Personality and migration:
A study of decision-making processes
in a geo-referenced framework

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Reinhard Alexander Weisser, M.Sc.

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Referent:	Prof. Dr. Patrick A. Puhani, Leibniz Universität Hannover
Korreferentin:	Prof. Dr. Susan Steiner, Leibniz Universität Hannover
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Abstract

This dissertation investigates the impact of personality on decision-making processes and choices in a migration context. In this regard, personality is assumed to affect the perception and evaluation of costs and returns related to migration. Personality is shaped by individual traits, such as risk attitude and time preference. Other relevant aspects are social preferences, the Big-Five personality traits, and individual adjustment capability. The research design relies on geo-referenced data, which enables a more accurate tracing of migration decisions and the detection of personality-related geographic preferences.

Spatial decision-making processes of prospective academics are the first research topic. It comprises various analyses regarding the formation of choice sets in the context of study location choice. Contrasting the findings from a preliminary selection stage with those from the final choice demonstrates individual traits to be of differing importance in the course of the decision-making process.

Final choices, potentially yielding a migratory event, are subsequently examined in a discrete choice framework. This approach facilitates the investigation of the effects of personality on location choices in presence of a high-dimensional destination space. Empirical results indicate the relevance of complex interactions of individual traits and destination characteristics, e.g., heterogeneous deterrence effects of distance or preference-related sorting patterns into more or less favourable labour markets. This modelling strategy is also transferred from a student sample to a population-representative sample, demonstrating its external validity.

Another topic is the impact of individual traits on the formation of salary expectations for prospectively high-skilled workers in various migration scenarios. Individual-specific evaluations of mobility-related costs are shown to inflate these salary expectations, and thus, they have the potential to lower the overall level of labour mobility in an economy.

Keywords: geo-referenced migration analysis, spatial decision-making processes, personality

Zusammenfassung

Diese Dissertation untersucht die Auswirkung von Persönlichkeitsmerkmalen auf Entscheidungsfindungsprozesse und konkrete Entscheidungen mit Migrationsbezug. In diesem Kontext ist anzunehmen, dass Persönlichkeitsaspekte die Wahrnehmung und Bewertung von Kosten und Erträgen beeinflussen. Wesentliche Persönlichkeitsbestandteile sind hierbei Risiko-, Zeit- und soziale Präferenzen. Weitere bedeutende Faktoren sind die Big-Five Persönlichkeitsmerkmale und individuelles Anpassungsvermögen. Das Forschungsdesign baut auf georeferenzierten Daten auf, welche ein präziseres Nachvollziehen von Migrationsentscheidungen und das Aufspüren von persönlichkeitsbezogenen geografischen Präferenzen ermöglichen.

Raumbezogene Entscheidungsfindungsprozesse zukünftiger Akademiker sind das erste Forschungsthema. Ein wesentlicher Schwerpunkt liegt hierbei auf dem Prozess der Vorauswahl möglicher Studienorte. Eine Gegenüberstellung der Ergebnisse in Bezug auf die Vorauswahl und die letztendliche Entscheidung zeigt, dass Persönlichkeitsmerkmale eine unterschiedlich starke Bedeutung innerhalb des gesamten Entscheidungsfindungsprozesses aufweisen.

Die endgültige Wahl eines Studienortes, die zu einem Migrationsereignis führen kann, wird anschließend mittels eines Discrete-Choice Modells eingehender betrachtet. Ein solcher Ansatz ermöglicht eine Untersuchung des Auswahlprozesses bei einer Vielzahl von möglichen Alternativen unter Berücksichtigung von Persönlichkeitsmerkmalen. Die empirischen Ergebnisse deuten auf ein komplexes Zusammenspiel von persönlichen und zielspezifischen Charakteristiken hin, z.B. eine heterogene Abschreckungswirkung von Distanz sowie persönlichkeitsspezifische Präferenzen in Bezug auf eine mehr oder minder vorteilhafte Arbeitsmarktsituation. Um die externe Validität dieser Analyse zu demonstrieren wird der analytische Ansatz zudem von einer Studierendenstichprobe auf eine bevölkerungsrepräsentative Stichprobe übertragen.

Ein weiteres Forschungsthema ist der Einfluss von Persönlichkeitsmerkmalen auf die Entwicklung von Gehaltserwartungen zukünftiger Hochqualifizierter in verschiedenen Migrationsszenarien. Individuelle Bewertungen mobilitätsbezogener Kosten erweisen sich als maßgeblich verantwortlich für massiv erhöhte Gehaltserwartungen und haben somit das Potenzial die Arbeitsmobilität innerhalb einer Ökonomie erheblich zu senken.

Schlagworte: georeferenzierte Migrationsanalyse, raumbezogene Entscheidungsfindungsprozesse, Persönlichkeit

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1 Main introduction

1.1 Motivation

Migration is a topic of continuous importance for policy-makers and civil societies alike. Inter-regional labour mobility can, at least partially, contribute to a reduction in regional disparities regarding unemployment rates or income levels (Niebuhr et al., 2012; Ederveen et al., 2007).[1] A persistent inflow of workers, however, may affect labour market outcomes of native workers asymmetrically: native workers at the lower end of the wage distribution may incur adverse wage effects whereas those in the upper part may benefit from it (Dustmann et al., 2013). Similarly, low-educated workers may be geographically displaced, while young highly-educated individuals are drawn to regions characterised by higher immigration levels (Mocetti and Porello, 2010).

Absolute flow numbers, however, are only half the truth: understanding skill-specific sorting patterns may be of interest to firms to enhance productivity (Boschma et al., 2009). Resulting productivity gains may further be influenced by the origin of high-skilled mobile workers (Timmermans and Boschma, 2014). This is also tangible evidence in favour of labour mobility being a highly relevant means of knowledge diffusion (Almeida and Kogut, 1999; Belenzon and Schankerman, 2013).

Student mobility is another important form of mobility to consider. Increasing numbers of students temporarily migrating, either to other countries or states, may raise the question with respect to the efficient design of the funding system (Delpierre and Verheyden, 2014) or regarding the possibility of increasing revenues by attracting non-resident students (Jaquette and Curs, 2015). As inversion of the argument, the impact of tuition fees on student mobility or ability-related sorting behaviour can be of interest as well (Dwenger et al., 2012). Such geographic sorting patterns eventually affect the local labour force's skill composition (Dotti et al., 2013) and a region's innovative potential (Faggian and McCann, 2006).

A third important aspect of migration concerns urban planners and local authorities: rising populations in metropolitan areas on the one hand, and declining populations in rural areas on the other, require a solution concerning the adequate provision of public infrastructure in the future. To predict future population dynamics or the impact of policy changes on the micro level, spatial microsimulation models are applied. Among other components, these microsimulation approaches rely on models of individual or household mobility (cf. Balas et al., 2005; Vencatasawmy et al., 1999), yet typically without integrating taste heterogeneity.

In either case, it is crucial to understand the mechanisms on the individual level behind these (temporary) population shifts. In this regard, a variety of different approaches have emerged in the discipline of economics over the decades in order to explain the various facets of individual human migration.

[1] Within this thesis, the terms 'migration' and 'mobility' are used interchangeably. Therefore, mobility always has a spatial connotation.

A most influential approach builds on income maximising agents (Sjaastad, 1962), basing their decision on a comparison of costs and returns related to migration. Others are based on Roy (1951) and evolve around location-specific returns to skills, i.e., a form of self-selection. Most migration models, e.g., gravity models (Leppel, 1993; Lewer and Van den Berg, 2008), account for an adverse effect of distance on migration likelihood or migration streams. This distance deterrence effect is mostly attributed to uncertainty or psychic costs (Schwartz, 1973), and not necessarily constant across socio-economic or socio-demographic groups (Mincer, 1978). A broader perspective of returns to migration is provided in the literature on compensating differentials (Graves and Linneman, 1979; Clark and Cosgrove, 1991) - utility maximising individuals integrate both location-specific income and amenity levels to evaluate migratory scenarios.

With an increasing availability of household panel data sets, more comprehensive models of individual mobility have been explored. Integrating individual factors beyond the standard socio-economic or socio-demographic factors, such as risk attitude (Jaeger et al., 2010) or Big-Five personality traits (Jokela, 2009), has proven to be insightful. Most studies, however, concentrate only on one specific individual trait. Typically, this is less a deliberate empirical modelling strategy than related to data paucity.

This dissertation addresses this data scarcity and then investigates mobility-related decision-making processes and choices of prospectively high-skilled individuals in light of a wider set of individual traits. The available data source furnishes information of individuals' geographic whereabouts at various points in their life. Such a geo-referenced approach not only enables tracing previous mobility episodes, but also linking decisions rather precisely to location-specific conditions. Eventually, this research examines the heterogeneous effects of subjectively perceived costs, e.g., psychic costs, and returns on the decision-making process at various stages within the selection of a study location. Another focus rests on the influence of individual traits on choices in a high-dimensional destination space, and hence accounts for complex decisions in a spatial context. This research additionally considers how individual traits may affect the design of incentives to induce labour mobility. Considering all of the above, this research contributes to the understanding of geographic sorting patterns of high-skilled individuals and the heterogeneous impact of personality-related evaluations on migration outcomes. At the same time, some consistent findings suggest potential measures on how to foster mobility of high-skilled individuals.

1.2 Synopsis

This thesis title clearly defines the fundamental requirements to be fulfilled in order for any data set to be used in this research. For one, it has to provide detailed information on individual characteristics like personality traits and preferences. In addition, the data should furnish information on the decision-making process itself, e.g., what alternatives have been explicitly considered and when. And last, in order to conduct an analysis in a spatial context, geographic reference points have to be available – only this allows accounting for location-specific features, which may also be relevant for the decision-making process.

Eventually, none of the available data sets allowed analyses on the level of detail necessary to answer the underlying research questions to the designated extent. In order to remedy this drawback, a survey on "Mobility, Expectations, Self-Assessment and Risk Attitude of Students" (Weisser, 2016a) was conducted. This survey is this thesis' main data source and therefore introduced in Chapter 2. Beyond a discussion of methodological and implementation aspects, this chapter also establishes the concept of geo-referenced mobility measurement and presents a descriptive survey overview.

Chapter 3 investigates the mobility inclination and observed geographic mobility of prospective high-skilled labour force participants at a transitional point in early adulthood. More precisely, this chapter examines how university entrants generate, in a first step, their initial choice set encompassing their most preferred alternative study locations. The analytical approach accounts for two dimensions in the choice set formation process: one relates to the choice set's scope, i.e., the number of alternative applications. The other addresses the degree of geographic dispersion of included alternatives in relation to an individual's origin, and consequently informs about a basic mobility inclination.

Individual traits, such as personality traits and time preferences display a high relevance regarding the size of the choice set: least patient individuals are found to form distinctly smaller initial choice sets, as do the least extraverted. Personality traits are also found to impose a certain geographic restriction on the considered alternatives in this set: individuals, who are least extraverted and least open to experience exhibit a noteworthy preference for alternatives closer to the familiar living environment. Moving to a more distant destination would especially evoke high (psychic) costs for these individuals. There is also evidence linking risk-aversion and impatience to an initial choice set consisting of alternatives clustered around the origin.

Contrasting the initial choice set formation stage with the realisation stage, a divergence between a basic inclination towards mobility and factual behaviour can be observed: a decision-maker's patience is only informative in the initial stage. The Big-Five trait agreeableness, related to trust, proves in turn only significant in the realisation stage when actual choices among a small number of alternatives are to be made.

Acknowledging the divergence between individuals' initial considerations and their final choices in a spatial context, Chapter 4 is dedicated to an analysis of complex decision processes in a high-dimensional destination space. The two pivotal research questions are how subjective evaluations affect students' location choices in presence of a plethora of potential destinations and how unobserved restrictions or inappropriate information sets may affect empirical answers to the first question. The second question is directly related to the sensitivity of random utility models regarding a misspecification of the underlying choice sets, i.e., what an analyst assumes to be the relevant destination space. Another critical aspect in the analysis of discrete (location) choices is a potential supply side restriction: observed choices, potentially leading to a migratory event, might only be imperfectly mirroring actual preferences if an admission process restricted the individual choice set further.

In order to evaluate the impact of insufficient information about the individual choice process - potentially resulting in an imprecise choice set definition - and general forms of misspecification in a conditional logit model, a simulation study is performed. This simulation mimics the real-world: not only do individuals consider choice sets of varying size, but their final choice set can also be restricted by unsuccessful applications, while both aspects are related to individual characteristics.

Simulation results demonstrate that estimates of individual choices in a demand and supply driven framework are sensitive with respect to the imposed information sets. Results tend to be distinctly biased if the choice set is defined too narrowly. Estimates are more precise if information on other, explicitly considered but eventually not chosen, alternatives is integrated.

Within the empirical analysis, spatial choices of beginning students have been shown to be distinctly influenced by urban characteristics, labour market conditions, and quality of life. The novelty of this research comes from demonstrating that these regional characteristics are valued differently across individuals, depending upon their personality and preferences: the most patient individuals are more likely to select a location offering better employment perspectives for high-skilled workers or higher potential income levels. The appeal of such labour market conditions, however, diminishes drastically if the distance to a potential destination increases. Price levels and population density exert a deterring effect which also fades over distance.

The relevance of interactions of location-specific conditions and individual characteristics has been proven to be robust. Moreover, the interaction of distance and personality attributes has revealed that the distance deterrence effect is not constant in an otherwise rather homogeneous population of prospective academics: perceived subjective costs and returns to mobility do not evenly increase in distance, but relative to individual traits and preferences.

The analyses of choices in a spatial context in Chapter 3 and 4 are based on a student sample, which offers an adequate leverage point to scrutinise complex decision patterns in rich behavioural models. A valid concern relates to a potential lack of external validity of the previous findings. This issue is concisely addressed in Chapter 5, which also illustrates the heavy trade-off between sample size and a richer behavioural modelling approach in population-representative data.

Using a specific geocoded data set from the German Socio-Economic Panel, this chapter investigates residential moving patterns and location choices of working-age decision-makers in the general population. The empirical findings emphasise the relevance of individual traits and preferences for analyses of spatial decision-making processes. Applying a similar modelling strategy as in Chapter 4, household mobility in the general population has been shown to follow similar patterns as student mobility. The further someone moved in the past, the more likely this person will choose a more distant destination in the future. There are also complex sorting patterns, for instance, according to which risk-averse individuals are reluctant to choose a destination afflicted by higher levels of unemployment. Yet concurrently, these individuals have a distinct preference to sort themselves into regional labour markets with a potentially more productive labour force, as indicated by a larger share of high-skilled workers.

Having shown that labour market characteristics can be already relevant at an early stage, i.e., university location choice, Chapter 6 casts a glance on potential post-graduation migration behaviour of the future high-skilled workers.

Pivotal points in this approach are expected mobility premiums which are sufficient to tip the scales in favour of moving to a geographically distinct location in four scenarios, i.e., interstate versus cross-border mobility and on-the-job search versus job search from unemployment. Investigating the overall distribution of ex ante premiums of future graduates has two major advantages: on the one hand, this approach proves to be directly informative about salary expectations (and potential mismatches in various scenarios) of the future entrants into the high-skilled labour market segment. On the other hand, this empirical strategy does not only integrate successful matches, as is typically observed in labour market data. Eventually, this approach is more informative with respect to factors inflating costs of mobility in a way that hardly any labour mobility occurs.

The mobility premiums are first derived within a theoretical model, accounting not only for location-specific amenity levels or labour market conditions, but also for heterogeneous personality and preference parameters. The derived hypotheses demonstrate that in presence of psychic costs or heterogeneous preferences, expected mobility premiums can remain positive even in an unemployment scenario.

The empirical approach, employing ordinary least squares and simultaneous quantile regressions, identifies social preferences and time preferences as the relevant factors regarding the formation of salary expectations. Moreover, the observed mobility premium further increases for individuals who perceive a specific migration path as especially risky.

Previous mobility experiences, in contrast, seem to act as dampening factors on expected mobility premiums. Individuals with international experience, who are more familiar with a changing environment and more likely to have devised adjustment strategies, expect distinctly smaller mobility premiums. Most importantly, this not only holds for cross-border scenarios but also for interstate labour mobility scenarios. An interesting implication of this finding is that labour mobility seems to be learnable to some extent.

2 Introduction to the main data source and the concept of geo-referenced mobility measurement

This chapter introduces the survey on "Mobility, Expectations, Self-Assessment and Risk Attitude of Students" (MESARAS 2013; Weisser, 2016a), which is also the major data source for subsequent econometric analyses of prospectively highly-qualified individuals' migration behaviour. In addition to an illustration of the survey's conceptual background, the survey design along with the sample's representativeness is discussed. Another subchapter is dedicated to a brief introduction to the concept to geo-referenced mobility measurement and its limitations. This chapter concludes with a presentation of the most essential descriptive findings from the survey, which serve as starting points for subsequent econometric analyses.

2.1 Presentation of the main data source: MESARAS 2013

2.1.1 Conceptual background

The MESARAS-survey has been conducted to provide information on a variety of individual traits and preferences in the context of detailed geo-referenced mobility events of prospectively highly-qualified individuals. In this regard, the mobility event of primary interest is the choice of a university location, yet previous mobility experiences are recorded as well. In either case, each mobility event can be assessed in a precise manner, i.e., as moving from one specific postal code area to another. Instead of being restricted to interpreting migration outcomes as a binary stay/move decision, individual mobility can be quantified based on covered distance.

Most importantly, the choice of a study location is for most respondents the first autonomous migration-related decision in their life. The observed outcome should thus reveal their preferences. At the same time, this decision, which occurs years before a future university graduate enters the primary labour market, is already indicative of subsequent migration behaviour (Perry, 2001; Groen, 2004; Busch and Weigert, 2010).

Hence, by linking detailed information on geo-referenced student mobility to individual characteristics and preferences, the survey enables an in-depth analysis of the actual decision-making processes in the context of internal migration. A special emphasis rests on personality traits, such as the Big-Five, risk attitude and time preferences which are usually not jointly available.[2]

To obtain an even more precise picture of such heterogeneous decision-making processes, the survey does explicitly address considered alternatives during the application stage and the final decision stage. This offers the opportunity to investigate first the formation of choice sets (Chapter 3)

[2] To a certain extent, these aspects are also covered by the German Socio-Economic Panel. Personality traits or time preferences, however, are not elicited on a yearly basis, but with a gap of several years. Considering the relatively low number of mobility events per year, the sample size may dwindle to a few hundred. This can be seen, for instance, in Chapter 5.

and in a second analytical step the final location choice (Chapter 4), both being contingent upon individual traits. Going one step further, the survey also offers some insights into individuals' inclination towards future mobility: conditional on varying labour market and migration scenarios, expected wage premiums to induce mobility can be investigated (Chapter 6).

Another merit of the MESARAS-data is that the chosen geo-referenced anchor points, i.e., postal code areas, enable accounting for local conditions in the decision-making processes as well. Individual migration-related decisions can thus be analysed in the context of internal and external factors alike.

2.1.2 Implementation mode

The survey had been conducted in October 2013, covering the first weeks of the winter term in the academic year 2013/2014. The economics and management departments of seven adjacent universities in three Federal States (Lower Saxony, Saxony-Anhalt and North-Rhine-Westphalia) participated: Bielefeld University (UBF), Clausthal University of Technology (TUC), TU Dortmund University (TDO), Martin-Luther-University Halle-Wittenberg (MLU), Gottfried Wilhelm Leibniz Universität Hannover (LUH), University of Münster (WWU) and Otto von Guericke University Magdeburg (OVG).[3]

These seven universities offer various economics undergraduate programmes with a substantial degree of thematic overlap in the curriculum. In a narrow sense, these economics programmes comprise Business Studies (BWL), Economic Studies (VWL), International Management (IM) and Economics and Business (Wiwi). Similar programmes, also including a substantial curriculum related to economics, are Business Informatics (Winf), Engineering Economics (Wing) and Economic Policy Journalism (Wipol. Jour.).

The reasons for choosing beginning students in an undergraduate economics study programme as the primary target group were threefold: beginning students in general, most likely enrolled for the first time, would have recently made a mostly autonomous mobility-related decision. Decision-relevant factors can therefore still be recalled. Second, the above-mentioned economics programmes in a narrow sense are available at almost all universities in Germany. Thus, observed location choices are not driven by the lack of actual alternatives, as might be the case for highly specialised study subjects. Instead, students could choose from a large number of potential destinations, all providing a rather homogeneous academic curriculum. Furthermore, students selecting themselves into these programmes are a relatively homogeneous group, characterised by a general interest in economic processes. Third and last, high enrolment figures in these programmes are indicative of potentially large sub-samples of student migrants. For analytical purposes, a substantial share of mobile individuals is required.

[3] The introduced abbreviations may or may not coincide with official abbreviations.

To ensure high participation rates, the unincentivised paper-based survey (Figure A2.1 in the appendix) has been directly implemented into the first month's programme: either into the departments' official orientation week for beginning students or into introductory lectures. Apart from the departments' heads, only the organisers of the orientation week or the respective lecturers knew beforehand about the survey. Due to the integration into the regular programme, participants did not incur additional costs of participation. This fostered accessibility and completion rates (Table 2.1).[4]

Table 2.1: Survey participation in the primary target group

		participants	participants (primary target group)		accessibility rate	completion rate
UBF	Bielefeld	191	181	(203)	89.2 %	97.2 %
TUC	Clausthal	68	67	(218)	30.7 %	99.1 %
TDO	Dortmund	408	348	(423)	82.3 %	98.0 %
MLU	Halle	518	399	(577)	69.2 %	97.8 %
LUH	Hannover	299	297	(520)	57.1 %	96.2 %
OVG	Magdeburg	396	373	(501)	74.5 %	98.5 %
WWU	Münster	709	643	(937)	68.6 %	97.8 %
Total		2589	2308	(3379)	68.3 %	97.7 %

Note: Numbers in brackets are official matriculation numbers.

More than two thirds of the corresponding population of beginning students enrolled in an economics bachelor programme participated in the survey. Simultaneously, the chosen implementation mode ensured extremely high completion rates.

2.1.3 Sample overview and representativeness

In the end, the primary target group comprised 2308 respondents in total. Amongst these, 91 % were enrolled in an economics-only programme, while the remaining nine percent were students with an economics-related major.

As the median age of 19 years (Table 2.2) suggests, the majority of respondents in the primary target group enrolled immediately after graduating from school. 44 % of the participants were female and 16 % of all respondents had previously already completed a vocational education. Most of these vocational degrees have been obtained in the sectors of banking and finance, industry and commerce.

Table 2.2: Socio-demographic characteristics of the primary target group

	n	mean	median	min	max
age (years)	2298	20.04	19	17	45
gender (female=1)	2308	0.44			
grade of university entry certificate (UEC)	2256	2.37	2.4	1.0	4.0
university semester enrolled	2110	1.29	1	1	21
completed vocational training (yes=1)	2302	0.16			

Approximately three out of four respondents applied for economics at other universities as well (Table 2.3). One third of the students also expressed a certain interest in non-economic programmes at other universities. 37.7 % eventually chose the study location which, to their knowledge, was the closest one.

[4] The accessibility rate is defined as the ratio of the number of participating students from the primary target group and the total number of matriculated students in the primary target group. The completion rate is defined as average number of answered items in the primary target group in relation to the total number of main items (111).

Table 2.3: Alternative study plans and preferences

	n	mean
application for economics programme at other universities (yes=1)	2306	0.737
application for other programmes at other universities (yes=1)	2294	0.340
current programme is the most preferred one (yes=1)	2301	0.851
current university is the most preferred one (yes=1)	2301	0.747
current university is the closest one (yes=1)	2294	0.377

20 % of all respondents applied for only one programme at one university. Two thirds mentioned that both university and study programme were their most preferred alternatives.

Table 2.4 reveals that there are gender-related sorting patterns concerning the selection of study programmes and destinations: whereas the share of female students in the business studies at WWU is close to 50 %, the corresponding share at MLU and OVG is 40 % or below. Such gender-specific patterns regarding the selection of universities and programmes are typically adequately mirrored in the survey samples. This congruence points to a substantial degree of representativeness of the MESARAS-data. For smaller sub-samples, i.e., programmes with lower total enrolment numbers or referring to enrolment of students from abroad, some deviations can be observed.

Table 2.4: Sample characteristics for the primary target group, by university and programme

university		study programme	n	share (%) of female students	mean age (in years)	share (%) of students from abroad
UBF	Bielefeld	Wiwi	181 (203)	40.3 (38.4)	19.9 (-)	1.7 (4.4)
TUC	Clausthal	BWL	58 (124)	31.0 (30.6)	21.5 (-)	5.2 (13.7)
		WIng	9 (95)	33.3 (23.2)	20.0 (-)	0 (20.0)
TDO	Dortmund	Wiwi	334 (404)	50.0 (47.5)	20.0 (20)	2.7 (7.7)
		Wipol. Jour.	14 (19)	35.7 (36.8)	20.1 (20)	0 (5.3)
MLU	Halle	BWL	280 (351)	42.5 (39.6)	20.1 (20.4)	1.8 (1.4)
		VWL	33 (41)	12.1 (14.6)	20.7 (21.4)	0 (0)
		Wiwi	85 (156)	47.1 (50.0)	20.4 (20.9)	2.4 (1.3)
		WInf	1 (29)	0 (13.8)	18 (22.1)	0 (3.5)
LUH	Hannover	Wiwi		*see Table 2.5*		
OVG	Magdeburg	BWL	204 (270)	38.7 (35.9)	19.9 (-)	1.0 (6.3)
		IM	101 (119)	71.3 (70.6)	19.5 (-)	0 (7.6)
		VWL	68 (112)	35.3 (37.5)	20.3 (-)	1.5 (4.5)
WWU	Münster	BWL	437 (617)	51.3 (48.5)	19.9 (20.5[5])	3.2 (4.4)
		VWL	107 (167)	29.9 (26.3)	19.7 (20.2)	4.7 (3.6)
		WInf	99 (153)	26.9 (17.6)	19.5 (20.2)	6.1 (8.5)
Full sample			2308 (3379)	44.1	20.0	2.7

Note: Numbers in brackets report respective population figures (if available), derived from universities' official matriculation data.

Drawing on more detailed administrative data, representativeness can be evaluated more precisely for the LUH-sample. This sample is characterised by a medium sample size and a relatively low accessibility rate, both increasing the likelihood that analyses based on this sample might only provide a distorted picture of the underlying population. In fact, a certain deviation in the share of female students can be observed (Table 2.5). Aside from this difference, mean age, the share of students from abroad and the average grade of the university entrance certificate (UEC) are hardly distinguishable across the MESARAS-sample and the population at LUH. Applying a Kolmogorov-Smirnov test for equality of distributions leads to a clear non-rejection of the null hypothesis: there are no significant distributional differences between the sample and the population data for age and

[5] Age was provided as 2013 minus year of birth. This leads to a slight overestimation of the average age for October 2013.

UEC grades. This result is reassuring, considering that individual educational achievement might be perceived as sensitive information, which introduces the risk of deliberate misreporting.

Table 2.5: Comparison between the MESARAS-sample and the population of the primary target group at LUH

	n	share (%) of female students	mean age (in years)	share (%) of students from abroad	mean grade of UEC
sample	297	46.13	20.30	2.37	2.49
population	520	41.35	20.36	2.88	2.50
KS (p-value)			1.000		0.966

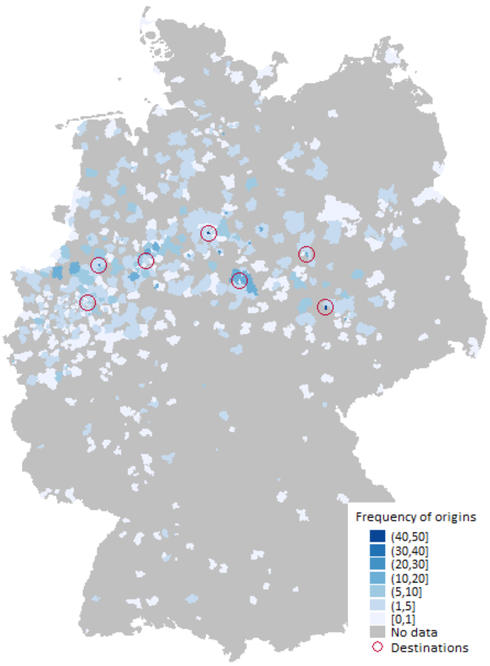
Note: For continuous variables, the exact p-value of the Kolmogorov-Smirnov test (H_0: equality of distributions) is reported.

Self-reported socio-demographic characteristics in the survey display a substantial degree of consistency between university-specific samples and corresponding populations. In light of high accessibility and overall questionnaire completion rates, the MESARAS-data can be assumed to be reasonably representative in order to serve as a foundation for subsequent econometric analyses.

2.2 Geo-referenced mobility measurement

Mobility events are identified as changing the centre of one's life from one small-scale spatial unit to another. The primary analytical units are the postal code areas where the individuals graduated from school. For one, these spatial units have been chosen for reasons of memorability. Moreover, whilst these locations plausibly functioned as social hubs, where young adults interacted with their peers, they were either identical or in very close proximity to actual places of residence. Thus, these specific locations are natural geo-referenceable anchor points. Figure 2.1 depicts the geographic distribution of origins of the primary target sample.

Figure 2.1: Geographic dispersion and relevance of origins



Note: 'Frequency of origins' refers to the number of students who originated from a specific postal code area and enrolled at any among the seven included universities (labelled 'destinations').

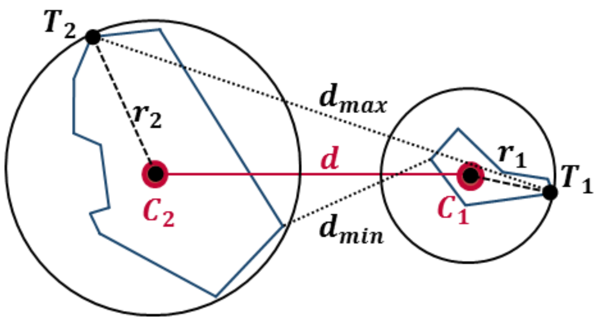
Whereas the universities in Bielefeld, Dortmund and Hannover mainly have a local or regional catchment area, the study locations Halle, Magdeburg and Muenster have been chosen more frequently by students from all over the country (Figure A2.2 in the appendix). The overall sample thus includes a substantial number of individuals, who actually exhibit a pronounced degree of mobility.

2.2.1 Measuring mobility based on geo-referenced data

Within the survey framework, participants have been repeatedly asked to report the respective postal code corresponding to a geographic anchor point, e.g., birthplace or other relevant locations during their life.[6] Changing postal codes allows identifying mobility events and the calculation of covered distances, with the latter being a proxy for costs of mobility.

Each postal code corresponds to a specific postal code area. In a predominantly rural area, such a postal code area may comprise several small towns. In the case of metropolitan areas, a single postal code area may just represent a city district. Using geographic information systems (GIS) data, reported postal code areas can be further defined based on the set of geographic coordinates, which constitutes an area's boundaries. Each postal code area can thus be represented by one or several polygons, where the respective corner points are exactly defined by their geographic longitude and latitude. Figure 2.2 presents schematics of the two postal code areas Vechta (left) and Hannover-City (right).

Figure 2.2: Graphical example for centroid-based distance calculations



The points C_1 and C_2 denote the two areas' centroids, which are the arithmetic mean of all coordinate points actually included in the respective postal code area. Calculating the distance d between these two centroids yields a measure of average distance between the two corresponding spatial units. In this example, distance d amounts to 106.865 kilometres.

Without knowing the exact address of an individual, this centroid-based distance provides a rather precise measure of individual mobility. To foster precision furthermore, this geographic distance is

[6] If the postal code was unknown, city and state (country) were adequate substitutes.

calculated as distance on the WGS 84 reference ellipsoid.[7] This accounts for the fact that the earth is not a perfect sphere, but an ellipsoid, which amplifies its relevance the further away from the equator the coordinates under considerations are.

2.2.2 Limits of precision and alternative measurement concepts

The proposed centroid-based distance measure allows tracking mobility rather accurately, yet it has its limitations as well: as Figure 2.2 indicates, it is most unlikely that an individual actually lived at C_1 and moved exactly to an address situated at C_2. Referring to the two extreme cases in the above depicted scenario, a person might cover $d_{max} = 115.436$ or just $d_{min} = 98.249$ km.

In either case, possible maximum deviations r_1 and r_2 tend to be much smaller in metropolitan areas with smaller postal code areas.[8] Any resulting localisation error ε will be in the interval $[-r_1 - r_2, r_1 + r_2]$. Eventually, $E[\varepsilon] \approx 0$ will prevail for the whole sample and evenly populated areas.

Consequently, the distance measure d is most precise for moves within a metropolitan area or from one highly urbanised and densely populated region to another. In these cases, the maximum possible deviation will be in the range of several hundred meters. Highest measurement errors result for moves between large postal code areas in less urbanised areas, if both origin and destination were located on (an extension of) line d. Larger postal code areas in rural regions, however, are also sparsely inhabited. This in turn lowers the likelihood of someone actually residing on the fringe, and thereby decreases the probability of maximum localisation error occurrences.

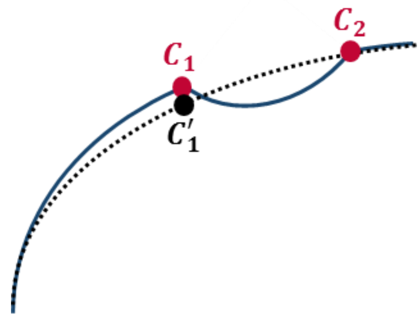
A second limitation originates from the earth's shape: geographic surface features, i.e., mountains and valleys, lead to a deviation from the perfect ellipsoid assumption. The actual distance to be covered in order to move from location C_1 to C_2 is depicted in blue in Figure 2.3. Yet, the applied algorithm calculates d as the distance between C_1' and C_2, following the curvature of the reference ellipsoid (black dotted curve). Using this algorithm to assess migration patterns in Germany, where maximum geographic distances remain below 1000 km, and considering topographical circumstances as well, the resulting approximation error remains in the range of some dozen meters.

Aggregate measurement errors, either caused by the localisation error in the centroid concept or due to the approximation error, will typically remain in the range of several hundred meters up to one-figure kilometres. To assess geographic mobility in a medium sized country, obtained measures based on postal code area's centroids yield a sufficiently precise distance measure.

[7] WGS 84 is the World Geodetic System standard, defined in 1984, which assumes a reference ellipsoid with an equatorial radius of 6378.137 kilometres and a flattening ratio of 298.257 (NIMA, 2000). Distance calculations have been performed in Stata 14.1, relying on the geodist-command. Centroids' coordinates have been derived based on imported GIS-data (using the Stata command shp2dta), providing geographic coordinates of polygons defining postal code areas. The original GIS-data was downloaded as Public Domain data (Metaspatial, 2013).

[8] For the metropolitan postal code area in Hannover, the observed maximum deviation is $r_1 = 1.565$ km; for the less urbanised postal code area Vechta the corresponding figure amounts to $r_2 = 7.737$ km.

Figure 2.3: Measurement error due to topographical deviations



Note: The black dotted curve represents the reference ellipsoid; the blue curve illustrates a topographical deviation.

A third potential drawback of using simple geographic distances refers to a lesser extent to the calculation procedure than to the perception of distance by decision-makers. Mobility-related costs are not necessarily determined by the shortest distance between an origin and a destination, but plausibly related to actual travel conditions, such as the road network. Depending on topographical features of the landscape, such as mountains or rivers, road distance may drastically differ from simple geographic distance. At the same time, travelling on a highway from one metropolitan area to another located at a distance of 100 kilometres will most likely be less time consuming than travelling the same distance on a country road. This points to two alternative distance measures, namely road distance and travel time.

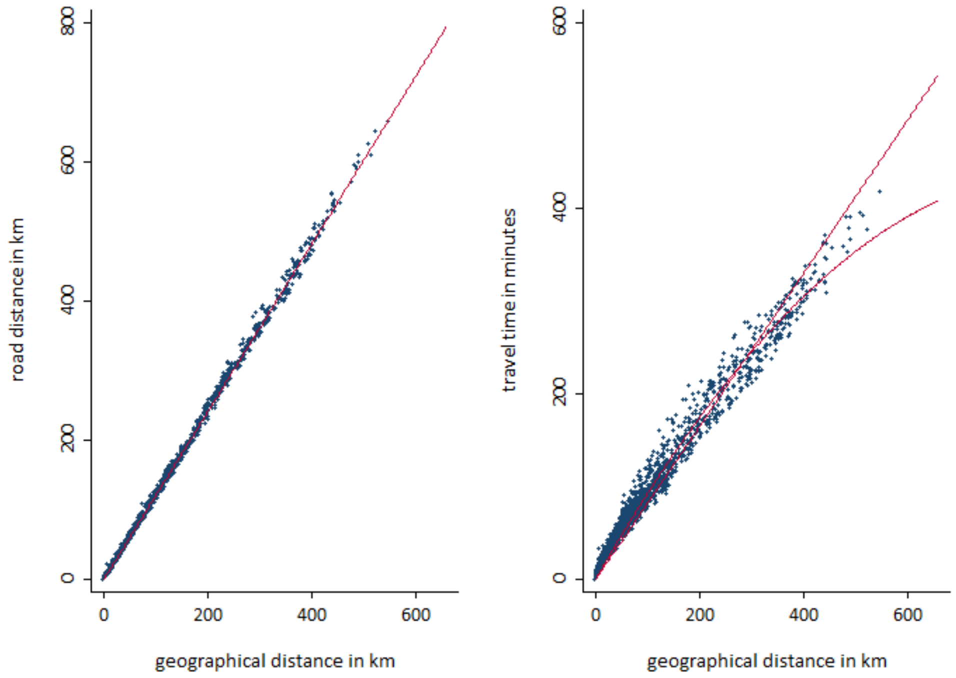
Another argument favouring these two alternative measures is the process of information acquisition and processing. If a decision-maker assesses means and costs of transportation between two locations, he or she will possibly extend the information search to the internet and not stick to ad-hoc heuristics. In such a case, routing tools typically provide information on both road distance and expected travel time.

In order to investigate subsequent analyses' robustness with respect to the applied distance concepts, I introduce alternative distance concepts from the so-called reachability-model provided by the Federal Institute for Research on Building, Urban Affairs, and Spatial Development (BBSR). Reference postal code areas are matched to one of over 11000 municipal or traffic cells from the reachability-model. For each observed mobility event, i.e., moving from one postal code area to another, road distance and travel time (in minutes) are thus made available as well.

The degree of correlation between geographic distance and road distance is extremely high, as the left panel in Figure 2.4 illustrates. The slope coefficient of the depicted regression line (red, constant omitted) amounts to 1.2071: irrespective of the overall travel distance, for every kilometre as the bird flies one has to travel 1.2 kilometres on roads. This strong correlation is directly related to the fine-meshed road network in Germany, which averts the necessity to take frequent detours.

The right panel illustrates the connection between geographic distance and travel time (on roads). The straight red line corresponds to the regression line from a linear regression; the curved line originates from a regression of travel time on geographic distance and its squared term. The slope coefficient of 0.8264 in the purely linear case implies that it takes on average 50 seconds on a road to cover one kilometre of geographic distance. For shorter distances, the model including a squared distance term displays a better fit. This corresponds to short-distance journeys taking place mainly within urban or metropolitan areas, thereby preventing reaching higher speed levels, which would have been otherwise possible on the highway in case of longer rides.

Figure 2.4: The conjunction of time and space



Note: All distance concepts refer to distances between individuals' origin and chosen university location. The sample comprises those 2208 individuals in the primary target group, for whom an explicit postal code area of origin in Germany could be identified.

If individuals pay special attention to travel time, which can be perceived as high opportunity costs of mobility, analytical results might notably differ compared to results based on simple geographic or road distance. To assess this issue, results' robustness regarding the underlying cost of mobility concept will be investigated in some of the subsequently performed analyses.

2.3 Descriptive findings on student mobility

The MESARAS-data offers at the descriptive level a variety of insights, which point towards avenues for further research. This paragraph presents some stylised facts, whereas a more complete documentation is provided in the project report (Weisser, 2016b).

Scrutinising the observed degree of mobility, which is measured as geographic distance between origin and chosen study location, no obvious gender-specific patterns emerge (Table 2.6). Female students typically came from further away to study at WWU, as compared to their male peers. The opposite was the case for students at MLU.

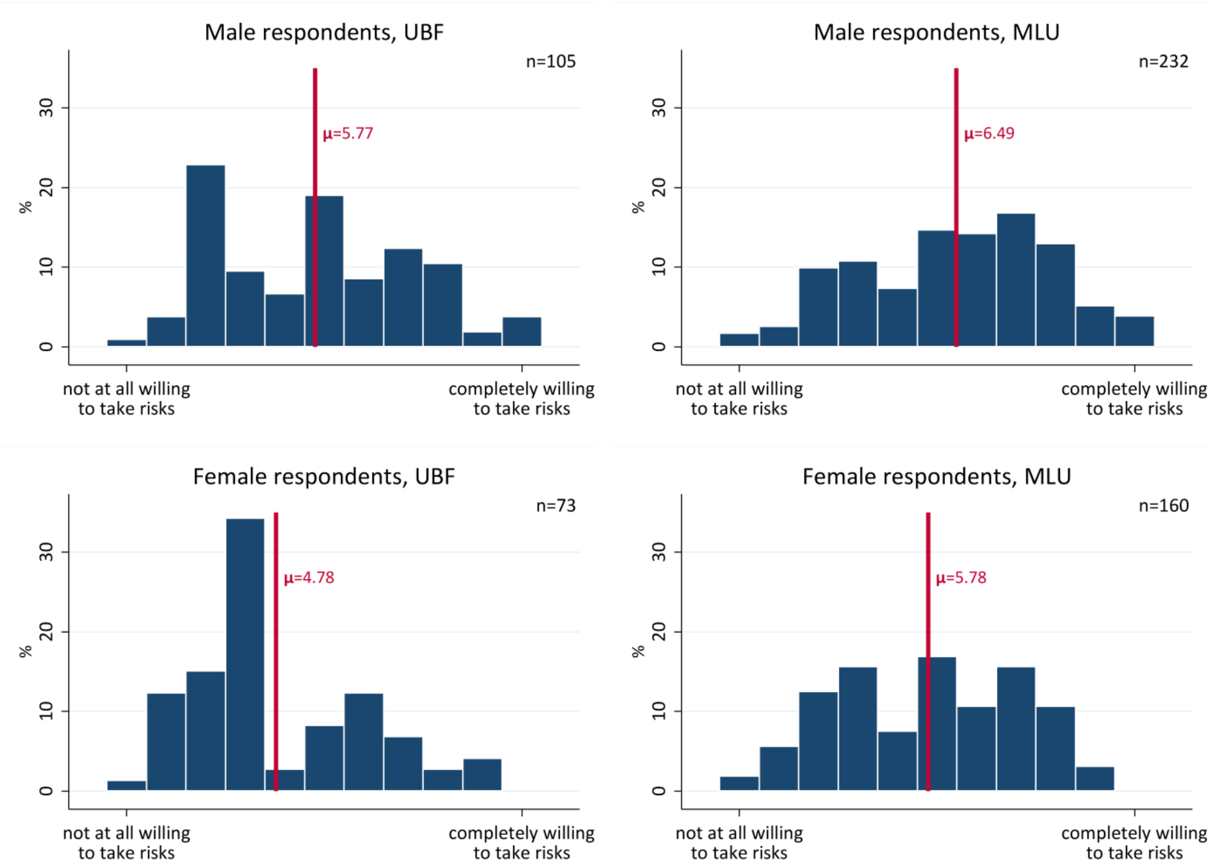
Table 2.6: Gender-specific differences in mobility

		gender	n	mean distance	median distance	KS (p-value)
UBF	Bielefeld	male (m)	106	31.9	24.0	0.844
		female (f)	71	36.9	24.9	
TUC	Clausthal	m	44	156.0	178.8	0.583
		f	19	117.8	85.6	
TDO	Dortmund	m	170	42.7	21.8	0.007***
		f	165	43.9	32.2	
MLU	Halle	m	220	153.1	130.3	0.070*
		f	157	130.7	110.3	
LUH	Hannover	m	157	60.5	32.6	0.479
		f	127	58.3	39.2	
OVG	Magdeburg	m	189	171.3	125.7	0.062*
		f	171	144.2	106.2	
WWU	Münster	m	351	101.7	78.4	0.023**
		f	260	115.4	94.6	
Full sample		m	1.236	104.1	63.9	0.226
		f	969	97.6	65.0	

Note: The exact p-value of the Kolmogorov-Smirnov test (H_0: equality of distributions for male and female students' mobility) is reported.

Irrespective of gender, some universities mainly attracted local students, whereas other universities were selected by students from all German states. If students with a similar interest in a specific study programme make such distinct location choices, the decision-making process has to be influenced by some other heterogeneous preferences or individual traits.

Figure 2.5: Willingness to take risks in general for students at UBF and MLU, by gender

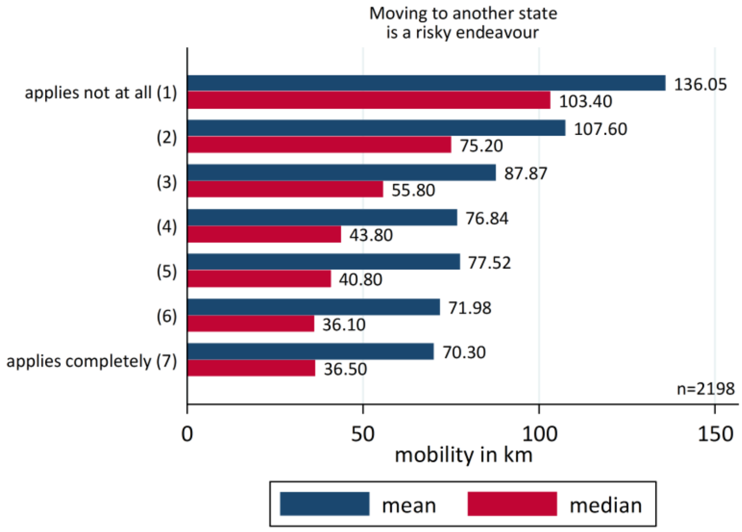


Note: μ indicates the corresponding mean.

One potentially relevant trait could be individual willingness to take risks: more risk-averse individuals might perceive the costs of going to a remote and unknown destination to be much higher than risk-loving individuals would. Consequently, rational individuals least willing to take risk would opt for a closer alternative. Figure 2.5 exemplifies this for the subsamples of male and female students at UBF and MLU, for whom the observed degrees of mobility were especially low or high, respectively.

In both subsamples, male students reported to be significantly more willing to take risks (on a 11-point scale) than their female fellow students. In addition, women enrolled at MLU displayed on average a risk attitude comparable to men enrolled at UBF. Seen in the context of overall higher degrees of mobility of students enrolled at MLU, this points to the existence of geographic sorting patterns according to individual risk attitude. For the full sample, Figure 2.6 demonstrates subjective risk perception to be an important aspect in the context of interstate migration.

Figure 2.6: Mobility and subjective risk assessment of an interstate move



This claim is supported by the results reported in Table 2.7: for both risk domains, referring to the willingness to take risks in general or in the career domain, the group of most risk-averse individuals opted on average for a much closer alternative than the most risk-loving individuals. Complementary to that, those respondents most willing to bear present costs for the sake of future returns are also the most mobile group. In the context of choosing a study location, inseparably associated with an investment in human capital, most patient individuals may plausibly enlarge their choice set by including more distant alternatives.

Table 2.7: Covered distance, by risk attitude and patience

	trait categorisation		
	low (score $< \mu - \sigma$)	medium ($\mu - \sigma \leq$ score $\leq \mu + \sigma$)	high (score $> \mu + \sigma$)
willingness to take risks (in general)	83.62	99.28	108.25
willingness to take risks (career domain)	87.93	96.26	106.51
willingness to bear present costs for future returns (patience)	92.50	94.64	115.74

Note: Reported figures are mean geographic distances in kilometres. The trait categorisations are based on a standardised version of the underlying scale variable. μ denotes the mean of this underlying variable; σ is the standard deviation.

Investigating mobility outcomes conditional on previous mobility experiences highlights notable differences as well. The more frequently someone moved during school, the larger on average the observed degree of mobility (Table 2.8). Considering that such a move during childhood or youth is initiated by parental decisions, its ramification regarding a first autonomous mobility-related decision is remarkable.

Table 2.8: Observed mobility and previous mobility experiences

		n	geographic distance (km)		road distance (km)		travel time (minutes)	
			mean	median	mean	median	mean	median
residential changes during school	not once	1693	97.1	62.3	117.1	75.3	88.1	65.5
	once	299	108.5	63.4	131.3	77.9	95.1	65.4
	twice	117	121.9	76.2	147.1	91.5	105.1	73.2
	three times	54	127.0	83.0	153.8	104.3	110.6	80.3
	more than three times	36	130.2	117.8	154.5	142.1	110.5	98.4
school exchange participation	no	1482	94.34	56.9	113.7	69.2	85.6	60.2
	yes	717	115.4	76.6	139.4	92.4	101.9	78.1
stay abroad (> 1 month)	no	1703	89.9	55.6	108.4	66.9	82.7	58.4
	yes	497	140.1	110.2	169.0	133.84	119.0	99.3

Participation in a school exchange programme or an extended stay abroad, i.e., events which have been at least partially under the volitional control of respondents, are also precursors of a more pronounced degree of mobility around university admittance. This prevails on application of any distance concept whatsoever. Previous mobility experiences, induced by external parental decisions or a possibly intrinsic motivation, seem to increase the individual capability of adjusting to new circumstances. This may lower the expected costs of mobility, thereby increasing the likelihood of someone selecting a more distant and less familiar destination.

Respondents were also asked to state how far they were willing to move in different scenarios: one referring to realising higher income perspectives and the other to increase employment perspectives in case of unemployment (Table 2.9).

Table 2.9: Willingness to move in varying scenarios, by willingness to take risks

scenario	higher income perspectives			better employment perspectives in case of unemployment		
	low willingness to take risks	medium willingness to take risks	high willingness to take risks	low willingness to take risks	medium willingness to take risks	high willingness to take risks
not at all	1.85%	1.13%	1.24%	5.82%	7.25%	8.61%
within the state	13.72%	8.41%	5.79%	13.49%	9.54%	7.38%
to another state	44.06%	38.16%	31.4%	40.21%	38.96%	27.51%
to another European country	24.54%	27.08%	22.73%	23.54%	23.72%	23.77%
to another country outside Europe	15.83%	25.22%	38.84%	16.93%	20.54%	30.74%
observations	379	1237	242	378	1227	244
Pearson χ^2		52.8771			27.6140	
prob > χ^2		0.0000			0.0010	

Note: The medium willingness to take risk category comprises all individuals rating themselves in the interval $[\mu - \sigma, \mu + \sigma]$. Pearson χ^2 tests the independence of columns and rows. Percentages are calculated by columns.

Across the two scenarios, the share of individuals willing to move to the most distant destination increases with their willingness to take risks. For higher income perspectives, 15.8 % of the most risk-averse respondents consider moving to another country outside of Europe. This fraction increases to

38.8 % in the group of the most risk loving individuals. It can also be observed that a non-negligible fraction of respondents does not consider moving at all, even if this could result in better employment perspectives when unemployed. This fraction increases with a rise in an individual's risk attitude from 5.8 % to 8.6 %.

This raises several interesting questions, such as whether unemployed immobile workers are indeed suffering from a lock-in effect in an adverse labour market or whether they are just less risk-averse and choose to stay and wait things out. Another question, to be addressed in Chapter 6, evolves around the design of individual specific mobility premiums, i.e., wage increases of sufficient size to induce labour mobility.

Big-Five personality traits represent a further angle to explain subjective valuations of mobility-related costs, eventually leading to differing location choices.[9] Introducing standardised scores, individuals can be categorised for each of the five personality traits into one of three distinct sub-groups: those scoring more than one standard deviation below the mean (low), those around the mean (medium) and those scoring more than one standard deviation above the mean (high). For all five traits one observes that covered distances increase or decrease monotonously (Table 2.10). Most open individuals chose on average a destination in 104.4 km distance, individuals of medium openness cover on average 98.08 km and those scoring lowest in the trait openness stay closest to their origin (87.88 km on average).

Table 2.10: Big-Five personality traits and observed mobility

	Big-Five categorisation		
	low (score $< \mu - \sigma$)	medium ($\mu - \sigma \leq$ score $\leq \mu + \sigma$)	high (score $> \mu + \sigma$)
Openness to experience	87.88	98.08	104.40
Extraversion	81.97	98.86	100.63
Neuroticism	104.33	97.18	92.60
Conscientiousness	102.35	98.38	86.65
Agreeableness	91.00	96.94	104.14

Note: Reported figures are mean geographic distances in kilometres.

All the preceding findings indicate that migration outcomes are driven by individual traits and preferences, since returns and costs to mobility are not identically evaluated across individuals. Especially risk attitude, but also previous mobility-related experiences seem to influence the decision-making process in the context of location choice of beginning students. In addition, observed mobility outcomes varied also concurrent with Big-Five personality traits and individual time preferences, respectively patience.

Building on these findings, the next chapters will explore this avenue further and investigate how heterogeneous individual traits actually affect the decision-making process itself.

[9] The Big-Five personality traits were constructed based on a Big-Five short inventory (Rammstedt and John, 2007), validated in a sample of German students. A more extensive version, e.g., the NEO Five-Factor Inventory (McCrae and Costa Jr., 2004) consisting of 60 items, could not be implemented in the survey due to time restrictions.

3 The agony of choice: Choice set formation and geographic mobility

3.1 Introduction

High tertiary education participation rates, ranging from 30 to 60 percent in Europe (King and Ruiz-Gelices, 2003), emphasize the relevance of university graduates as an integral part of the labour force. In light of a strong interrelation between student and post-graduation migratory trajectories (Perry, 2001; Busch and Weigert, 2010), understanding the behaviour of mobile individuals at the verge of commencing tertiary education promises valuable insights into their prospective migration patterns. In the case of Germany, for instance, flows between Eastern and Western states are strongly driven by the mobile young (Hunt, 2006), hence the behaviour of young cohorts is highly relevant for understanding population dynamics.

Aside from enhancing human capital or functioning as economic incubators, universities also attract students, whose talents can then be put to use immediately after graduation in the surrounding geographic labour market (Dotti et al., 2013). This may translate into a direct link between initial student migration and the strengthening of the human capital pool in a region (Winters, 2011), eventually enhancing local growth perspectives.

Ultimately, migration outcomes over the years are driven to a considerable extent by students' initial choices regarding where to apply and where to study. The underlying decision-making process, in turn, is governed by individual-specific valuations, pointing to the relevance of earlier experiences and individual traits, moulding a kind of migrant personality (Boneva and Frieze, 2001; Frieze et al., 2006).

The main goal of this study is to develop a more precise picture of the facets, defining such a migrant personality and to investigate its impact on the decision-making process within the selection of a study location. This is done by explicitly integrating personality traits, individual experiences and valuations. Another contribution of this work is to shed some light on intra-national student mobility outside the Anglo-American realm, which is a rather sparsely discussed phenomenon (Prazers, 2013).

This work draws on a survey, specifically designed to provide information not only on final choices, but also on preferences within the application process. Based on information about actually considered alternatives, this research's premise is the partitioning of the decision-making process into two distinct stages: first, the formation of an initial choice set, including the most preferred location alternatives in a planning phase. The second realisation stage is defined by the selection of one alternative, from a potentially exogenously restricted choice set, yielding a migration outcome.

The formation stage is analysed to determine individual traits explaining the initial choice set's scope. In this domain, individual traits such as patience and extraversion are positively related to the number of considered alternatives. Moreover, by applying a geo-referenced framework, the chosen analytical procedure acknowledges that internal migration is a truly distance-based phenomenon. An analysis of the components in the initial choice set demonstrates that the personality trait openness gains in importance: individuals least open to experiences exhibit a distinct initial preference for alternatives closer to their origin. At the realisation stage, though, some of the initially significant factors lose their relevance: decision-making processes at the planning stage and the subsequent final choice in a migratory context do not necessarily coincide.

A pivotal implication of these findings is that individuals evaluate costs of mobility differently, and thus exhibit differing sensitivities to moving distance. A potential mechanism is an increased adjustment capability to new circumstances, mitigating costs of mobility. This adjustment capability seems to be nurtured by previous mobility experiences, such as moves during childhood or exchange participation.

The remainder of this study is organised as follows: Chapter 3.2 reviews the state of research, both related to important mechanisms fostering geographic mobility in general and with reference to students in particular. Chapter 3.3 introduces the specific data set and highlights some descriptive statistics. Individual choice set formation, accounting for the impact of heterogeneously perceived costs of mobility, is investigated in Chapter 3.4. Observed migration outcomes, and thus actual location choices from alternatives in the initial choice set are investigated in Chapter 3.5. Chapter 3.6 concludes and points out remaining questions.

3.2 Literature review

This review discusses first relevant findings with respect to individual migration in general and turns then to the specific topic of student mobility.

Decision-making processes in a migration context are often modelled based on a cost-benefit comparison where individuals are assumed to relocate in order to maximize their expected utility. This is a reliable framework to analyse migratory dynamics in the general population as well as in subgroups, e.g., consisting of students. One of the first to describe migration as an outcome of an individual's comparison of expected earnings differentials between various destinations (the monetary returns to migration) and associated costs of migration was Sjaastad (1962). Aside from monetary costs, he also recognized the importance of 'psychic costs', originating from social and family attachment.

Returns to migration can have a monetary dimension, e.g., attaining a steeper post-migration earnings path (for Germany, see Kratz and Brüderl, 2013 or Lehmer and Ludsteck, 2011), or a nonpecuniary dimension if a higher living standard can be realised. In the latter case, a sufficient improvement regarding the availability of amenities can not only compensate for associated costs of migration, but even a decline in income (Graves and Linneman, 1979; Roback, 1982; Graves, 1983).

Both costs and returns to migration are a matter of subjective perception, shaped by personality and individual experiences. Risk and time preferences, for instance, might lead to heterogeneous valuations of objectively identical income or amenity differentials between two locations.

Since time preferences vary across individuals, these potential returns to mobility will be valued differently (Frederick et al., 2002). Eventually, this impacts on migration intentions (Van Dalen and Henkens, 2012) and can individually affect optimal job search intensity (DellaVigna and Paserman, 2005), and hence also labour market outcomes. Risk attitude is a relevant individual trait as well, since more pronounced risk-aversion may inflate perceived costs of mobility and reduce the overall willingness to migrate. More risk-seeking individuals, on the other hand, are more likely to migrate in general (Jaeger et al., 2010; Nowotny, 2010), and even when controlling for cultural distance (Bauernschuster et al., 2014), thereby imposing possible additional costs of relocation.

Costs of mobility have a clearly defined monetary aspect: relocating and moving a household's belonging requires, for instance, commissioning a moving company. Associated transportation costs increase typically with distance. In conjunction with the plain fact that long-distance moves are more likely to result in the crossing of national or administrative borders, causing additional transaction costs, distance is the most consistent predictor in the context of geographic mobility: this holds for aggregate cross-border migration flows (Mayda, 2010; Belot and Everdeen, 2012) and internationally mobile students (Rodríguez González et al., 2011; Brezis and Soueri, 2011; Perkins and Neumayer, 2014; Beine et al., 2014).

Portending a certain similarity of the underlying decision process in case of cross-border and intra-national migration, this distance deterrence effect is also observed at the intra-national or regional level for students (McHugh and Morgan, 1984; Leppel, 1993; Alm and Winters, 2009; Cooke and Boyle, 2011) or for the general population (Stillwell, 2005; Schwartz, 1973; Biagi et al., 2011), and even when distance enters a model as rather imprecise proxy.[10]

Aside from directly measurable transportation or transaction costs, there exist psychic costs of migration, plausibly rising with distance as well.[11] These psychic costs of migration could manifest as acculturative stress, associated to a "lowered mental health status (specifically confusion, anxiety, depression), feelings of marginality and alienation, heightened psychosomatic symptom level, and identity confusion" (Berry et al., 1987). Loss of emotional support in the origin country, and the (perceived) migratory distance are also associated with increased depression risk (Vega et al., 1987). Whilst some acculturative stress scenarios might only be relevant in the context of cross-border movement, and hence also cross-culture migration (e.g., language issues[12]), others might already result in the case of internal migration: moving from a rural area, with its specific social environment, to an urban centre, characterised by a larger degree of anonymity, can lead to feelings of alienation as well.

[10] The issue of (categorical) distance proxies is discussed more intensively in a related context by Ham et al. (2011). Their results, i.e., estimates' magnitude and significance, are highly sensitive with respect to the implemented distance proxy (indicating moving types).

[11] In the notation of Sjaastad (1962) these could be represented by a monetary equivalent, defined as a maximum amount of a region-specific income which could be taxed away before the respective individual decides to migrate to an alternative region.

[12] In this regard, language proficiency could facilitate the process of cultural adjustment and thus lower possible distress in a host country, causing less frequent occurrence of schizophrenia amongst migrant samples (Bhugra, 2004).

The assessment of mobility-related stress is thus likely to vary based on psychological features. Several links between personality and geographic mobility might be considered. Frieze and Li (2010), for example, suggested place attachment, sensation seeking or sociability. Sensation seeking individuals might reap some benefits just by moving to a new and possibly exciting environment which in turn would mitigate perceived psychic costs.[13] More sociable types might experience the (initial) loss of social interaction as more burdensome on moving to an unfamiliar place. There is empirical evidence that the Big-Five traits openness and extraversion, indicating a more pronounced ability to establish new connections, are indeed associated with a higher internal migration probability (Jokela, 2009) or a more pronounced and qualification-dependent inclination towards future mobility (Canache et al., 2013). Higher aggregate levels of neuroticism or conscientiousness have been found to be indicative of larger shares of non-mobile households on the state-level (McCann, 2015).

There is also evidence that distress is perceived more frequently by women (Mirowsky and Ross, 1995) or that women are psychologically more responsive to geographic relocation, hence are more prone to depression than men thereafter (Magdol, 2002). In addition, distance to their kin and social contacts play a more prominent role for women to avoid psychological distress.

Aside from personality or preferences in a wider sense, educational attainment is another individual trait which is found to influence individuals' willingness to migrate substantially.[14] Skilled workers, i.e., college graduates, display higher propensities to migrate (Wozniak, 2010; Tolbert et al., 2009), and migrate over longer distances over the course of their life (Hillmert, 2008). Tertiary educated individuals are likely to realise higher returns from migrating to a spatially different labour market, yielding a comparative advantage regarding mobility decisions (Dahl, 2002; Carlsen et al., 2013).[15] Geographic mobility, however, does not only translate into monetary returns: Coté (1997) showed that migration per se is conducive to higher occupational status during the middle age, even when controlling for socio-economic and regional characteristics.

Since highly educated individuals, i.e., former students, are a most mobile group once they entered the labour force, an immediate question refers to the origin and the evolution of such distinct migration behaviour.

In this regard, McHugh and Morgan (1984) or Dotti et al. (2013) presented evidence that student migration is influenced by economic conditions in the destination state too, for instance, as students might explore local employment options after graduation. Furthermore, students seem to be

[13] In principle, it could also be interpreted as non-monetary return from moving.

[14] Even when only conditioning on years of schooling Machin et al. (2012) uncovered for Norwegian data a positive relationship between education and migration: one additional year is associated with an increase of the migration rate of 0.15 percentage point.

[15] More interestingly, due to this comparative advantage, the related "self-selection of higher educated individuals to states with higher returns to education generally leads to *upward* biases in OLS estimates of the returns to education in state-specific labor markets" (Dahl, 2002, p. 2367).

attracted to destinations with better amenities (Mixon and Hsing, 1994[16]; Cooke and Boyle, 2011), thus behaving similarly to non-student migrants.

There is also a strong linkage between student mobility and subsequent individual mobility over the course of life. Studying abroad fosters the likelihood of starting into the working life abroad (Parey and Waldinger, 2011; Oosterbeek and Webbink, 2011; Di Pietro, 2012). This is possibly related to the acquisition of country-specific labour market information, especially language skills (Fertig and Schmidt, 2002). Moreover it seems to affect the decision-making process of men and women asymmetrically (Balaz and Williams, 2011), in a way that only female border-crossing migrants were more risk-loving.

Yet, previous cross-border student mobility may also foster inter-regional mobility after graduation (Franck et al., 2012). Persisting migration patterns, i.e., a tendency to linger at a specific location or in a geographic region that had once been chosen for study purposes, is frequently documented, even when potential alternative study destinations are accounted for (Groen, 2004). A consistent picture emerges for the US and Germany: around two thirds of the students tend to stay in the states they graduated from university (Perry, 2001; Busch and Weigert, 2010).

In the context of university choices, the evidence on the impact of institutional quality is mixed. Students are in so far selective, yet some choose to migrate in order to attend highly ranked institutions, others due to availability of admission (Mixon and Hsing, 1994; Cooke and Boyle, 2011). The potential impact of a ranking on preferences may also vary across types of university, whereas higher research activities may even deter potential students (Drewes and Michael, 2006). Sá et al. (2004) reported no unambiguous impact of educational quality, but of programme quantity on the decision to enrol at a specific university. Excluding flagship institutions with relatively few enrolled students, there is also evidence in favour of students choosing study places mostly based on availability and costs (Faggian and McCann, 2006).

The initial decision regarding where to study may also be partially 'inherited', i.e., children whose father graduated from university (and thus typically displayed some mobility inclination) were also more willing to move to another region for study purposes or subsequent labour market entry (Belfield and Morris, 1999). Such mobility patterns, shaped by parental decisions, "may represent an acquired predisposition due possibly to increased knowledge and decreased psychological inhibitions to moving away from a known environment" (Black, 1983, p. 274). This highlights a direct line between parental decisions, individual adjustment capability and the perception of psychic costs to mobility.

Though the literature typically focuses on one specific individual feature, the evidence suggests various individual traits, which may have a joint impact on the decision-making process in a migration context.

[16] In their specification, specific sportive activities constitute relevant consumption factors for students.

3.3 Data and descriptive statistics

Data on precisely traced geographic mobility, personality traits, attitudes and mobility-related preferences has proven to be scarcely available. This is especially true when it comes to the availability of information on considered, but eventually discarded alternatives in the decision process. Therefore, to investigate the process of choice set formation more closely, a data set was compiled which enables a joint evaluation of the previously stated non-standard characteristics and geo-referenced migration profiles. This data set is briefly introduced in this chapter.

3.3.1 Introduction to the data source

The underlying data source is a survey on "Mobility, Expectations, Self-Assessment and Risk Attitude of Students" (MESARAS 2013; Weisser, 2016a), a specifically designed survey which took place in October 2013.

Its primary target group consisted of 2308 university students, enrolled in an undergraduate economics study programme in the first semester at one of seven adjacent universities in northern and middle Germany. This sample has been further restricted for the purpose of this study to include only those who commenced their university life, hence just chose a location within the preceding weeks. Furthermore, students whose postal code or city of origin could not unambiguously be identified were excluded. This also pertained to students from abroad. Yet, this restriction ensures that covered distances could be precisely determined, based on centroids in a close-meshed spatial grid. Eventually, this study's target sample comprised 1861 individuals. The descriptive statistics for this sample are provided in Table A3.1 and Table A3.2 (in the appendix).

The reason for such a specific target group was twofold: first, students can be seen as valid representatives of prospective highly qualified individuals, since after graduation they immediately enter the labour force as highly educated workers. Second, for most of the beginning students the choice of a study place is the first autonomous mobility-related decision whereas earlier mobility experiences resulted mainly from parental decisions.

As a core feature, the specific design of the MESARAS-survey allows the identification of previous residential or other relevant locations (birth place, school entrance, alternative study locations) on the level of postal code areas. This in turn enables to capture mobility as a truly distance related phenomenon, on a scale of kilometres. Instead of being restricted to assessing mobility as a rather binary yes/no decision, mobility becomes a quantifiable item. In case of participants' choice of a specific study location, the observed mobility-related decision can be expressed as distance between chosen university and origin, identified by previous residence or the respective city, where respondents graduated from school.[17]

[17] Any geographical distance between two postal code areas is measured as the ellipsoid distance between the two respective areas' centroids. A more detailed description of the calculation procedure, alternative distance concepts (such as road distance and travel time) and a discussion of potential drawbacks can be found in Weisser (2016b, p. 7-9).

The restriction to economic study programmes resulted from methodological considerations and follows the idea that this approach minimises the likelihood of the occurrence of unobservable, but varying characteristics of an unknown distribution within the population. In addition, focusing on a specific family of programmes, represented at virtually every university, ensures that students truly had a choice between several locations and observed mobility was in fact a choice and not an inevitable outcome, related to the non-existence of alternatives.[18]

The overarching goal of the target-specific survey was to provide genuine, geo-referenced data with a high response rate. The latter was ensured by implementation into faculties' orientation weeks or first month's lectures. For the participating faculties of the seven universities, the sample covered in total 68.3 percent of all enrolled first semester students.[19] Using administrative enrolment data, a high degree of representativeness could be established.

Thus, except for basic aspects of self-selection into a special study programme, the respondents can be assumed to be rather representative for young adults at the beginning of their (academic) career. Their inclination towards mobility, and some aspects of the choice of the place of study, should be related to their preferences for social interactions and expectations. In this regard, participants have been explicitly asked to report the importance of various potential criteria which might have influenced their decision, e.g., by determining their perception of psychic costs.

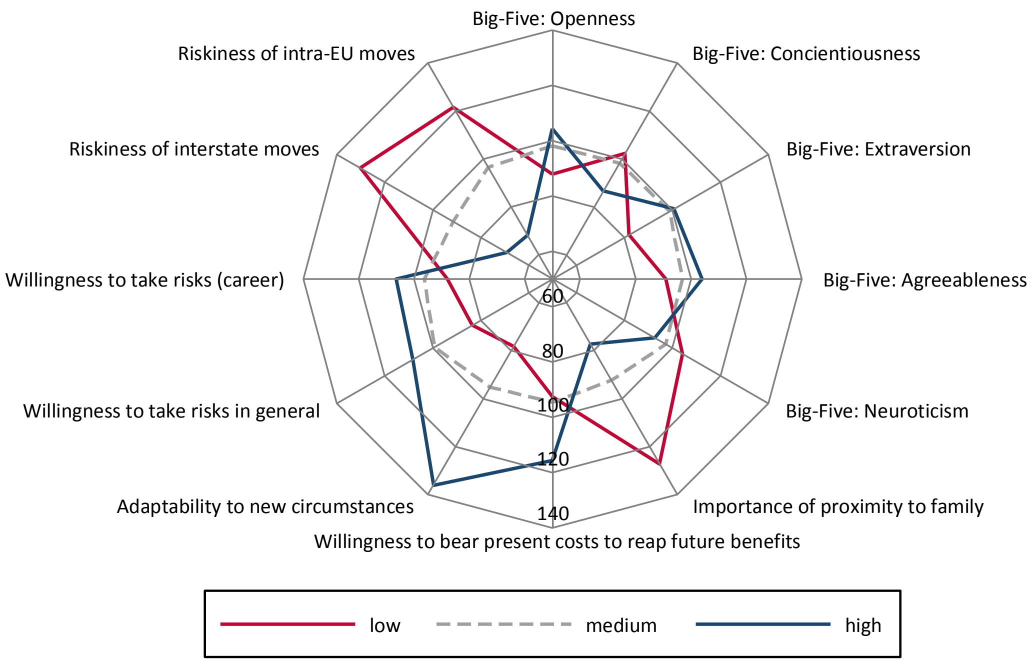
3.3.2 A quick glance on students' mobility

How mobile are young academics in the sample, or in other words, how far do they go? The answer is on average exactly 97.15 kilometres.[20] One quarter of them stays within a radius of 24.8 kilometres around their previous centre of life, thereby opting for the closest available alternative in most cases. In fact, respondents in the sample display profoundly varying degrees of mobility, which is measured as geographic distance between university location and previous residence, i.e., the location where someone acquired the university entrance certificate (UEC). Descriptive statistics in Figure 3.1 portray the average observed mobility for three basic subgroups: those scoring distinctly below the mean (red) on a given scale, those around the sample mean (grey) and those notably above the mean (blue).[21]

Participants scoring more than one standard deviation below the mean on the Big-Five trait neuroticism are found, on average, in more remote study locations. The distinction between groups is even larger regarding the importance of proximity to family: those stating that such proximity was of relatively higher importance chose on average universities much closer to the familiar environment.

[18] Subsequently presented empirical specifications explicitly accommodate the existence of alternatives.
[19] More details, also with respect to representativeness, can be found in Weisser (2016b).
[20] Notably, this figure is almost twice as large as the distance for young academics (age 20) in the 1964 birth cohort from the West German Life History Study, reported by Hillmert (2008). Across all educational groups, Leopold et al. (2012) reported an average distance of 68.4 kilometres for young adults' move-outs from the parental household.
[21] The categorisation based on individual scores, respectively the distance to the sample mean, fosters comparability across different underlying scales.

Figure 3.1: Average observed mobility in kilometres, conditional on individual traits and preferences



Note: The three depicted groups refer to a classification based on standardised scores, such that 'medium' refers to those scoring within one standard deviation around the mean and 'high' ('low') comprises those more than one standard deviation above (below) the mean. The sample size varies across dimensions between 1811 and 1853.

Groupings by individual risk attitude typically yield the expected outcomes: individual expressing a high willingness to take risks, both in general and in the career domain, display a higher level of observed mobility. The perception of a move's riskiness is also indicative of specific mobility patterns. Individuals who see interstate moves as a rather risky endeavour eventually enrol, on average, at institutions in 69 kilometres distance. Those who assess interstate moves to be hardly a risky endeavour, in contrast, are almost twice as mobile.

Overall, the degree of inter-group variation in the sample highlights several personality traits to be plausible candidates in the investigation of determinants of individual mobility and initial choice set formation.

3.4 Destination choice sets of heterogeneous decision-makers

Voluntary migration always involves a choice, i.e., in the simplest case it boils down to the question 'to move or not to move'. This naturally requires the existence of a possible alternative to the current location. For a worker, such a move could be induced by an alternative job offer in a remote city. In the case of a young adult, the choice of a study location would define the destination.

Within the overall decision-making process, comprising an application and a realisation stage, prospective students consider various choice sets. Any observable migration outcome, however, depends eventually on these choice sets. Therefore, analysing the generation of these initial choice sets is crucial for a better understanding of individual mobility patterns.

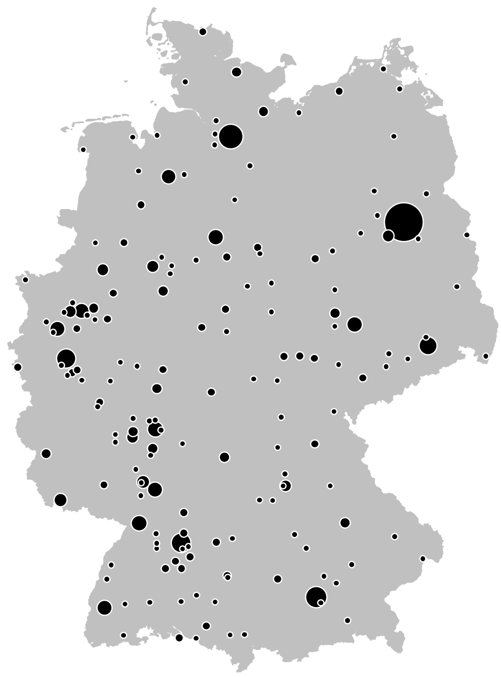
The concept and the generation of initial choice sets are discussed in Chapter 3.4.1. Subsequently, the impact of personality on this individual-specific formation process is empirically investigated: first, regarding the initial choice set's scope (Chapter 3.4.2), and then regarding the set's components (Chapter 3.4.3).

3.4.1 Generating the initial choice set of location alternatives

The analytical starting point is a prospective student's basic choice set, comprising all potentially relevant locations. In fact, the most basic choice set for prospective academics consists of 399 officially recognised institutions of higher education in Germany, offering 9801 undergraduate programmes in total.[22]

However, for an assessment of geographic mobility, being the focus of this work, the actual maximum number of alternative destinations can be narrowed down: the relevant destination space comprises 164 cities in Germany (Figure 3.2).

Figure 3.2: Proportional geographic distribution of German higher education institutions



Note: The relative size of the black dots corresponds to the number of institutions of higher education at the respective postal code area.

Ultimately, there are 71 distinct university locations offering a full-time bachelor programme with economics or business focus in a broader sense.[23] Curricula in these programmes have a high degree of overlap since these bachelor programmes consist of introductory courses with the same basic

[22] Figures taken from HRK (2015).

[23] Included programmes are business administration, economics, economics and business administration, engineering economics and business informatics. Taking universities of applied sciences into account as well yields 164 unique locations.

content.[24] For example, the interest in a specific field of study would be satisfied by studying business at a university in the north in the same way as by choosing to study in southern Germany.[25]

Based on their study preferences, but also influenced by other individual preferences and valuations, individuals select a subset of institutions, where they apply for. This yields the initial choice set C_0, which is characterised by a quantitative and a qualitative aspect.

The first is taken into account by the total number of applications (n_{C_0}) at any institution (offering an economics programme) at any of the 164 alternative destinations. The initial choice set's scope informs about 'how many' alternatives are considered. It captures whether someone puts all of his or her eggs into one basket by applying only for the preferred institution and location or hedges against refusals by sending out applications to multiple institutions.

The qualitative aspect is evaluated in the distance dimension (d).[26] It refers to the choice set's components and introduces the aspect of geographic mobility by investigating 'where' designated study alternatives are located. Regardless of the actual number of applications, preselected alternatives inform about the fundamental willingness to migrate over specific distances.

Figure 3.3 (left panel) shows a graphical representation of the initial choice set of a fictitious individual. This fictitious individual considered nine destinations and applied at institutions on site. The remaining alternatives were irrelevant in this individual's decision-making process.

Typically, only the university's location where someone finally enrolled (labelled 'U') is observed. The study's underlying data source, however, preserves additional information: in addition to the finally chosen alternative, the observed initial choice set also comprises the three most preferred destinations someone applied for.

Similarly, the three favoured locations, from where the admissions have been granted, are known too. Together with the eventually selected destination, these alternatives constitute the observed final choice set (C_1). Depending on the institutions' admission process, the most preferred alternatives in the initial and the final choice set do not need to coincide.

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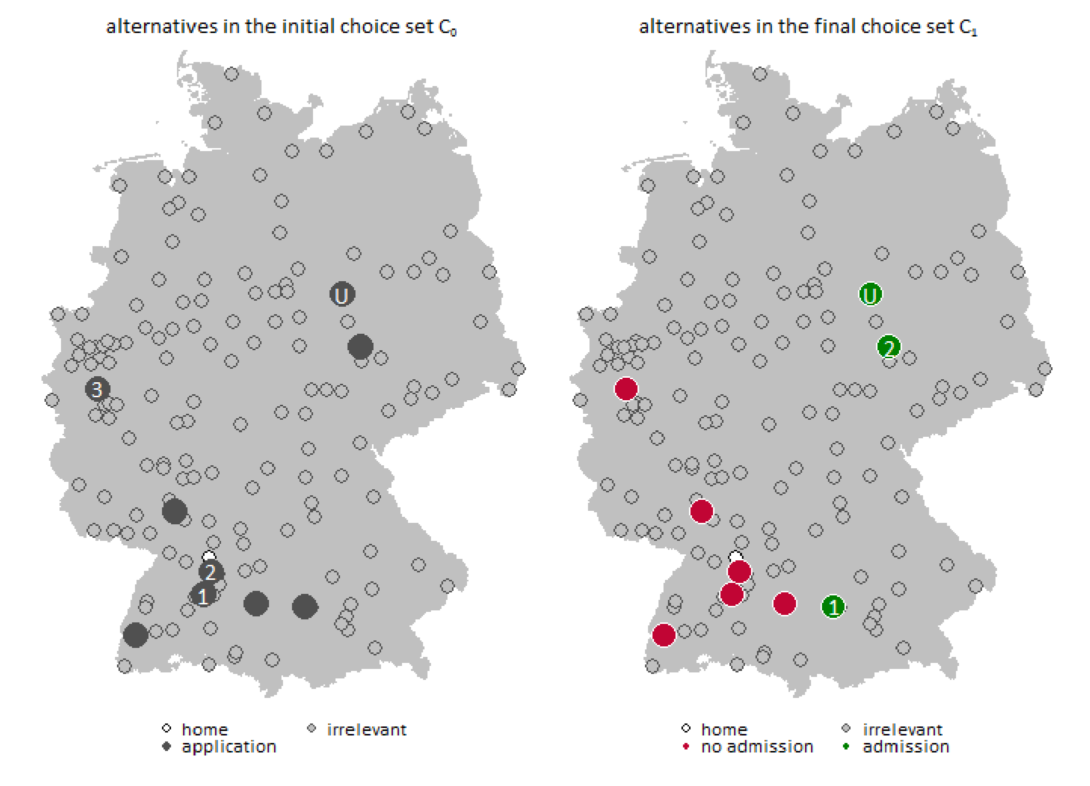
[24] Typically the curriculum comprises introductions to micro- and macro-economics, basic statistics, and some business-related courses, e.g., accounting or investment.

[25] One could make the case that identically labelled courses at two universities were still to differ with respect to the teaching content. Yet, course design and priorities rely mainly on the lecturer in the end, hence, specific course content may vary much stronger at one institution if the lecturer changes.

[26] In principle, university rankings constitute a plausible qualitative dimension as well. However, there are several drawbacks. National rankings, i.e., the so-called Handelsblatt-Ranking or the CHE-Ranking, suffer from two major shortcomings: first, many (large) universities do not participate. Second, the ranking involves dimensions that are not necessarily relevant for students, such as publications in case of the Handelsblatt-Ranking. The CHE-Ranking 2011 comprises additional research dimensions, e.g., third-party funding or number of doctorates, but is also of insufficient coverage when it comes to the dimension of student evaluations: here, the sample of ranked universities collapses to one third for economics (Berghoff et al., 2011). Resorting to international rankings does not solve this issue: The Shanghai-Ranking 2012, for instance, mentions only 5 German universities in the Top 200 of economics departments (ShanghaiRanking Consultancy, 2012). Another conceptual limitation is concatenated to the elicitation mode of considered alternatives: being easily recalled, alternatives have typically been stated on the city level. This impedes a meaningful mapping of rankings in case of destinations with several universities.

Figure 3.3: The sets of possible location alternatives



Compiled information on multiple applications in the initial choice set provides several insights: even if someone was less inclined to study at location X, compared to location Y, he or she would only apply for X if this alternative was at least acceptable as a sort of makeshift destination. Consequently, such an auxiliary alternative contains relevant information regarding a person's preferences. A comparable reasoning can be used in case of applications for locations where admission chances are considered to be slim – the initial decision to apply nevertheless still provides valuable information regarding potential location choices, hence the theoretical willingness to migrate.

3.4.2 The initial choice set's scope

The choice set's scope analysis, investigating factors influencing the number of alternative applications, relies on two slightly different measures: one captures the general existence of alternative applications for economics programmes (n_{i,C_0}), a second accounts only for the number of applications at institutions at geographically distinct locations (n^L_{i,C_0}).

Table 3.1: Choice sets' scope – all alternatives and geographically distinct alternatives

		n^L_{i,C_0} (number of geographically distinct alternatives in C_0)				
		1	2	3	≥ 4	$\sum$
n_{i,C_0} (total number of alternatives in C_0)	1	375				375
	2	3	153			156
	3	1	32	208		241
	≥ 4	0	10	128	807	945
	$\sum$	379	195	336	807	1717

Approximately one fifth of the subjects (375) had an initial choice set consisting of a sole alternative, whereas 80 % of all individuals in the target sample (1342) had sent out at least one additional application for an economics programme (Table 3.1). 13 % (174) amongst these, however, did not proportionally increase their initial choice set in a geographic sense: they instead applied for multiple economics programme at the same location.

The chosen approach allows differentiating between individuals, for instance, one initially applying at three alternative locations and the other initially selecting three programmes at one location. Both individuals display a comparable degree of hedging against non-admission ($n_{1,C_0} = n_{2,C_0} = 3$). Yet, the second individual displays a much stronger geographic preference for one specific location ($n^L_{1,C_0} = 3, n^L_{2,C_0} = 1$). Albeit highly correlated on the aggregate level, the underlying concepts of these two measures of the initial choice sets' scope vary notably: the second definition (n^L_{i,C_0}) introduces a stronger notion of geographic variation, and thus possibly accounts for a higher latent willingness to display migration behaviour.

Recognising this conceptual difference, the subsequent econometric analysis contrasts both measures. Each of the two ordinal variables was additionally transformed into a binary version (b_{i,C_0}, b^L_{i,C_0}), set equal to one if more than one application was reported, and zero otherwise. This allows investigating the basic hedging aspect and an evaluation of the outcomes' robustness with respect to the embodied recording threshold of four alternatives.

The simple binary scope measures are analysed in a logit and an ordinary least squares (OLS) framework. The first maps predicted probabilities exactly into the corresponding space, between 0 and 1. Calculated odds ratios (OR) in the logit specification inform directly about whether a change of an explanatory variable increases the odds of an individual forming an initial choice set with at least one actual alternative. The linear probability model (LPM) yields some directly interpretable coefficients and may serve as benchmark for additional estimations, accounting for the existence of potentially endogenous variables.

In case of the logit model, the probability of observing a choice set of size two or larger is given as

$$P\left(b_{C_0} = 1\middle|X\right) = P\left(b^*_{C_0} > 0\middle|X\right) = P(X'\beta + \varepsilon > 0) = \frac{\exp(X'\beta)}{1+\exp(X'\beta)} = \Lambda(X'\beta) \qquad (3.1)$$

with $\Lambda(.)$ as logistic cumulative distribution function.

The corresponding linear probability model (LPM) can be represented as

$$b_{C_0} = X'\beta + \varepsilon$$

In contrast to the standard OLS model, based on the conditional mean assumption $E[\varepsilon|X] = 0$, the error term in the LPM is not independent from X, even if all regressors were in principle exogenous: since b_{C_0} is restricted to be either zero or one, the corresponding error is either $1 - X'\beta$ or $X'\beta$, and thus heteroskedastic by design.[27] Nevertheless, the LPM offers some insight into basic relationships, and in contrast to the logit model, a marginal effect of interest is not dependent on other variables.

The matrix X of explanatory variables consists of socio-demographic variables and an ability measure (the average grade of the university entrance certificate). Furthermore, risk and time preferences are

[27] This issue is addressed by applying standard errors, which are robust with respect to heteroscedasticity.

included, measured as willingness to take risks and as willingness to bear present costs for future benefits (labelled as patience), respectively. The set of individual traits is enriched by the Big-Five personality traits, a measure of adaptability and the importance of proximity to reference persons. The latter two exert potentially a certain impact on psychic costs associated with a migratory decision (Schwartz, 1973).

Individual traits enter the models usually in a standardised manner, such that three distinct types of individuals can be identified: those scoring distinctly below the sample average (score $< \mu - \sigma$), the reference-type or average-type individuals ($\mu - \sigma \leq$ score $\leq \mu + \sigma$), and those scoring at least one standard deviation above the mean (score $> \mu + \sigma$). This approach allows detecting non-linear links between individual traits and aspects of the choice set formation.

Referring to the subset of individual traits, self-reported adaptability to new circumstance and the importance of proximity to reference persons might violate the exogeneity condition. This would be the case, if these concepts capture the underlying concept of psychic costs only to a certain extent, hence are recorded with a substantial measurement error, introducing correlation with the error term. To account for this possibility, these two variables are instrumented in some of the following specifications. As instruments serve previous mobility experiences, which are arguably exogenous in the analysed decision framework. Furthermore, they should only affect the investigated outcomes indirectly (via the first stage) and not exert any immediate impact on the scrutinised outcome.[28]

The first instrument is a measure of residential mobility during childhood and youth. Such a decision, before the individual came of age, had been made by the individual's parents. Therefore, it is reasonable to assume that it could not be affected by the individual's plans to apply at one or several universities. Such moves, during a child's formative years, might strengthen the importance of reference persons in the family, hence validating this instrument's usage in a first stage.

Participation in a short-term (school) exchange programme is the second instrument. Typically, such programmes are designed for juveniles and participation requires parental permission. At the same time, parental encouragement might induce teenagers to participate in the first place, i.e., participation is largely at parents' discretion. Eventually, being confronted with another environment in a different cultural setting might foster individual flexibility and thus justify this instrument's application to instrument adjustment capability in a first stage.

With respect to the binary assessment of the choice set's scope, three main results – robust across all estimation methods and model specifications – emerge (Table 3.2, Table A3.3 and Table A3.5).

[28] Admittedly, this exclusion restriction can be challenged. Another concern relates to a potential correlation between the instruments and unobserved variables, such as household income. More affluent households might have distinct mobility patterns and offer their children more study opportunities, e.g., in more expensive study locations. The variable 'academic household' is supposed to partially account for parental households which are characterised by higher income levels.

Table 3.2: Choice set's scope – binary approach, all applications

dependent variable	b_{i,C_0}									
estimation method	logit		LPM		IV (2nd stage)		LPM		IV (2nd stage)	
	OR	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.
gender (female)	1.2486	(0.1724)	0.0316	(0.0211)	-0.0032	(0.0355)	0.0159	(0.0216)	-0.0375	(0.0420)
age	0.8292***	(0.0402)	-0.0321***	(0.0088)	-0.0365***	(0.0093)	-0.0266***	(0.0086)	-0.0321***	(0.0096)
academic household	1.2294	(0.1599)	0.0324	(0.0200)	0.0384	(0.0291)	0.0284	(0.0203)	0.0329	(0.0327)
uec grade	0.7829**	(0.0964)	-0.0361*	(0.0198)	-0.0494	(0.0303)	-0.0635***	(0.0197)	-0.0952***	(0.0362)
vocational training	1.4602	(0.3548)	0.0656	(0.0413)	0.0635	(0.0478)	0.0653	(0.0409)	0.0638	(0.0524)
partnership										
< 6 months	1.2918	(0.3471)	0.0330	(0.0349)	-0.0075	(0.0480)	0.0306	(0.0358)	-0.0308	(0.0562)
6-12 months	0.8122	(0.1807)	-0.0321	(0.0382)	-0.0829	(0.0559)	-0.0498	(0.0391)	-0.1265*	(0.0656)
1-2 years	0.7379	(0.1554)	-0.0520	(0.0369)	-0.0640	(0.0532)	-0.0603	(0.0379)	-0.0734	(0.0588)
2-3 years	1.0564	(0.2367)	0.0071	(0.0340)	0.0061	(0.0432)	0.0053	(0.0356)	0.0065	(0.0500)
> 3 years	1.1566	(0.2923)	0.0185	(0.0382)	-0.0012	(0.0486)	0.0180	(0.0395)	-0.0107	(0.0558)
risk attitude (career domain)										
score $< \mu - \sigma$	1.0411	(0.1999)	0.0079	(0.0288)	0.0068	(0.0362)	0.0156	(0.0301)	0.0189	(0.0424)
score $> \mu + \sigma$	0.7801	(0.1199)	-0.0404	(0.0250)	-0.0282	(0.0370)	-0.0358	(0.0251)	-0.0204	(0.0421)
patience										
score $< \mu - \sigma$	0.5498***	(0.0850)	-0.1040***	(0.0287)	-0.1075***	(0.0314)	-0.1023***	(0.0294)	-0.1051***	(0.0352)
score $> \mu + \sigma$	1.2921	(0.2430)	0.0380	(0.0261)	0.0145	(0.0485)	0.0339	(0.0261)	-0.0098	(0.0556)
extraversion										
score $< \mu - \sigma$	0.8235	(0.1524)	-0.0351	(0.0324)	0.0348	(0.0881)	-0.0484	(0.0334)	0.0681	(0.1009)
score $> \mu + \sigma$	0.9493	(0.1517)	-0.0076	(0.0249)	-0.0588	(0.0532)	-0.0097	(0.0254)	-0.0950	(0.0639)
neuroticism										
score $< \mu - \sigma$	0.7939	(0.1586)	-0.0384	(0.0323)	-0.1103	(0.0681)	-0.0341	(0.0324)	-0.1464*	(0.0786)
score $> \mu + \sigma$	0.8685	(0.1546)	-0.0211	(0.0281)	0.0177	(0.0489)	-0.0129	(0.0284)	0.0534	(0.0575)
openness										
score $< \mu - \sigma$	0.9343	(0.1476)	-0.0119	(0.0252)	-0.0131	(0.0334)	-0.0054	(0.0259)	-0.0024	(0.0374)
score $> \mu + \sigma$	0.9672	(0.1647)	-0.0054	(0.0268)	-0.0126	(0.0333)	-0.0314	(0.0271)	-0.0501	(0.0392)
conscientiousness										
score $< \mu - \sigma$	0.9922	(0.1565)	-0.0036	(0.0260)	0.0158	(0.0315)	-0.0021	(0.0267)	0.0266	(0.0359)
score $> \mu + \sigma$	0.8903	(0.1536)	-0.0186	(0.0259)	-0.0459	(0.0358)	-0.0221	(0.0265)	-0.0666	(0.0415)
agreeableness										
score $< \mu - \sigma$	0.9964	(0.1562)	-0.0030	(0.0252)	0.0286	(0.0354)	-0.0138	(0.0260)	0.0297	(0.0408)
score $> \mu + \sigma$	1.0767	(0.1863)	0.0097	(0.0262)	-0.0195	(0.0351)	0.0093	(0.0269)	-0.0362	(0.0412)
x_1^{endog}: imp. of prox. (family)	1.0351	(0.0422)	0.0052	(0.0063)	0.0940	(0.0729)	0.0032	(0.0063)	0.1283	(0.0852)
x_2^{endog}: adaptability	1.1660***	(0.0527)	0.0242***	(0.0074)	0.1353	(0.0962)	0.0213***	(0.0076)	0.2000*	(0.1144)
origin controls	✓		✓		✓					
constant	✓		✓		✓		✓		✓	
observations	1717		1717		1717		1717		1717	
log likelihood	-828.00									
df	30		30		30		26		26	
LR χ^2 / F / Wald χ^2	126.32		4.84		119.19		3.08		54.32	
prob > χ^2/ prob > F	0.0000		0.0000		0.0000		0.0000		0.0009	
pseudo R^2 / adjusted R^2	0.0813		0.0707				0.0312			
exogeneity test										
Wooldridge (1995) score test					2.40 (p=0.3011)				4.59 (p=0.1006)	
regression based test					1.18 (p=0.3078)				2.27 (p=0.1038)	
1st stage: x_1^{endog}										
F(model)					6.51 (p=0.0000)				7.14 (p=0.0000)	
z_1: res. move during school					-0.3671 ***	(0.0976)			-0.3568 ***	(0.0972)
z_2: exchange participation					-0.1225	(0.0820)			-0.1278	(0.0814)
F(instruments)					8.38 (p=0.0002)				8.18 (p=0.0004)	
1st stage: x_2^{endog}										
F(model)					13.54 (p=0.0000)				15.08 (p=0.0000)	
z_1: res. move during school					0.0068	(0.0857)			0.0143	(0.0857)
z_2: exchange participation					0.2505***	(0.0744)			0.2421 ***	(0.0742)
F(instruments)					5.71 (p=0.0034)				5.36 (p=0.0048)	
weak instrument test										
F^{crit} $(\alpha = 0.10)$					7.03				7.03	
F^{crit} $(\alpha = 0.15)$					4.58				4.58	
F^{crit} $(\alpha = 0.20)$					3.95				3.95	

*** p<0.01, ** p<0.05, * p<0.1

Note: The two potentially endogenous variables (importance of proximity to family and adaptability to new circumstance) enter the specifications as quasi continuous variables (on a scale from 1 to 7). This modification is implemented with regard to the first stage estimations. LR χ^2 refers to the logit model, F to the LPM and Wald χ^2 to the IV estimation. F^{crit}report the critical values of Stock and Yogo's (2005) weak instrument test, assuming i.i.d. error structure.

Older individuals are less likely to form a choice set larger than size one. Since older age implies fewer years in the labour market to reap additional study-related returns to education, such a smaller choice set may thus be the rational outcome. Least patient individuals exhibit a lower likelihood of forming a larger choice set as well: increasing admission likelihood, eventually rising expected future returns due to this human capital investment, is less valued by those individuals with a stronger preference for the present. Lastly, individuals displaying a weaker educational performance, indicated by a worse grade, also opt less frequently for a larger initial choice set. Amongst the potentially endogenous regressors, only adaptability displays a significant correlation with the dependent variable in the logit baseline specifications. More adaptable persons have higher odds of forming a larger choice set.

The third and fifth columns in Table 3.2 and Table A3.3 (in the appendix) report second stage results from a two-stage least squares estimation, one controlling for origin characteristics. Testing for exogeneity of the two potentially endogenous regressors (x_1^{endog} and x_2^{endog}) leads to a non-rejection of the Null hypothesis: regarding the scope of choice sets, these two variables do not display a significant correlation with the error term.

In either case, the chosen instruments display a significant joint explanatory power in a respective first stage, as indicated by the corresponding F-statistics (labelled 'F(instruments)'). Previous residential moves during childhood are a significant predictor of a less pronounced relevance of proximity to family, whereas participation in a school exchange programme does not display explanatory power on its own. Findings are reversed when it comes to the first stage explaining high degrees of adaptability: only the participation in a short-term exchange is significant, but not previous residential moves. Referring to a more formal test, Stock and Yogo (2005) characterise a set of instruments to be weak if a Wald test with a nominal confidence level of 5% exhibits an actual rejection rate of up to 10 % (15 % or 20 %). In case of the first potentially endogenous variable x_1^{endog}, the respective first stage F-statistics of 8.38 and 8.18 are above the provided critical F-values for an actual α of 10 %.[29] This implies that the Null hypothesis of weak instruments can be rejected. For the second potentially endogenous regressor, with first stage F-statistics of 5.71 and 5.36, the Null can only be rejected at an actual α equal to 15%.

A direct comparison of OLS and IV estimates for the potentially endogenous regressors delivers evidence for the occurrence of attenuation bias: OLS estimates are always closer to zero than corresponding IV estimates. Ultimately, only adaptability shows explanatory power in the IV specification's second stage without origin controls: a one scale-point increase in adaptability raises the probability that an individual has a choice set of at least size two by approximately 20 %.

Though the binary scope approach yields valuable insights, and allows addressing the issue of potentially endogenous variables, it discards some of the information actually available in n_{C_0} and $n_{C_0}^L$. There might be a qualitative difference, not only with respect to whether someone has an initial

[29] Provided critical F-statistics assume errors to be in fact i.i.d. Derived first stage F-statistics in a robust specification, however, are smaller than the corresponding statistics from estimations without robust variance-covariance matrix. Therefore, smaller F-statistics in the robust case make non-rejection of the Null of weak instruments even more likely.

choice set of size two or one, but also having one, two, three and four or more alternatives included into the initial choice set. This is addressed in the following subsection by applying ordered logit estimations. In an ordered logit model, the probability that an individual's choice set is of scope $n_{C_0} = j \; \forall \; j = 1{,}2{,}3{,}4$ is represented by

$$P\left(n_{i,C_0} = j\right) = P\left(\kappa_{j-1} < X'\beta + \varepsilon \leq \kappa_j\right) = \frac{1}{1+\exp(-\kappa_j + X'\beta)} - \frac{1}{1+\exp(-\kappa_{j-1}X'\beta)}\,. \quad (3.2)$$

It corresponds to the probability that the estimated linear function $X'\beta$ plus the logistically distributed error term ε are within the interval defined by the upper cut point κ_j and lower cut point κ_{j-1}. An underlying assumption is the so-called proportional odds or parallel regression assumption: it requires that the functional relation between an explanatory variable and the observed outcome is not conditional on the outcome level. In other words, irrespective of whether one compares individuals with $n_{C_0} = 1$ to those with $n_{C_0} \in [2{,}4]$ or alternatively the group with $n_{C_0} \in [1{,}2]$ to those individuals with $n_{C_0} \in [3{,}4]$, the coefficients obtained from the first comparison should not significantly differ from those derived in the second comparison. This assumption can be tested, for instance, using the Brant (1990) or the Wolfe-Gould (1998) test.

An alternative approach to investigate the initial choice set's scope, treating the number of applications as actual count data, is a censored Poisson regression model. It accounts for a censoring at four or more alternatives in the initial choice set. More precisely, the right-censored Poisson regression model actually addresses the number of additional 'hedging' applications, such that the corresponding dependent variable is $n_{C_0}^P = n_{C_0} - 1$ and the censoring occurs at the threshold $T = n_{C_0}^P = 3$.[30]

Based on a Poisson distribution, the probability to observe $n_{C_0}^P = j$ is given by

$$P\left(n_{C_0}^P = j \middle| X\right) = \frac{e^{-\lambda}\lambda^j}{j!} = P_j \quad (3.3)$$

where λ is the distribution's mean. Following Greene (2012, p. 812-814), the corresponding conditional mean function, assuming a right-censored Poisson distribution, is represented by

$$E\left[n_{C_0}^P \middle| X\right] = T - \textstyle\sum_{j=0}^{T-1}(T-j)P_j \quad (3.4)$$

It represents the expected incidence of an additional application, beyond the first one, which also consequently extends the initial choice set's scope.

Results for the more precise scope measures (Table 3.3 and Table A3.4) support the main findings from the binary scope analysis. The odds of having a larger initial choice set are 0.8739 (0.9001) times smaller if age was to increase by one year.[31] Similarly, derived incidence rate ratios (IRR) in the censored Poisson model indicate that if an individual was to age one year, his incidence rate of

[30] This modification of the dependent variable is required so the outcome can be modelled as originating from a Poisson process, i.e., $n_{C_0}^P = 0$ has to be possible.

[31] Across specifications, both the Brant and the Wolf-Gould test lead to non-rejection (at a confidence level of 5 % or 10%) of the Null hypothesis of no coefficient differences across outcome groupings. This indicates that the proportional odds assumption is not violated.

hedging applications would change by a factor of 0.9367 (0.9498) ceteris paribus. This is equivalent to a decrease of 6.33 % (5.02 %) in the expected count of such applications.

In addition to the trait patience, the Big-Five trait extraversion now displays explanatory power too: least extraverted individuals have 0.62 times smaller odds of sending additional applications. In terms of incidence rates of hedging applications, these individuals have an approximately 20 % lower expected incidence rate than the reference group. Since the dependent variables in the ordinal and count approaches account for a wider scope, these findings indicate that least extraverted individuals perceive their returns to a larger choice set, and thus to a higher overall admission likelihood, as not as positive as their peers in the reference group.

Table 3.3: Choice set's scope – ordinal approach, all applications

dependent variable	n_{i,C_0}				n^P_{i,C_0}			
estimation method	ologit				cpoisson			
	OR	s.e.	OR	s.e.	IRR	s.e.	IRR	s.e.
gender (female)	1.1813	(0.1275)	1.0811	(0.1150)	1.0804	(0.0521)	1.0438	(0.0503)
age	0.8739***	(0.0328)	0.9001***	(0.0321)	0.9367 ***	(0.0169)	0.9498 ***	(0.0165)
academic household	1.1929*	(0.1203)	1.1551	(0.1141)	1.0771 *	(0.0481)	1.0690	(0.0477)
uec grade	0.8861	(0.0858)	0.7733***	(0.0729)	0.9482	(0.0411)	0.8868 ***	(0.0372)
vocational training	1.2765	(0.2382)	1.2780	(0.2302)	1.1209	(0.0988)	1.1207	(0.0974)
partnership								
< 6 months	0.9569	(0.1700)	0.9435	(0.1647)	0.9907	(0.0796)	0.9775	(0.0788)
6-12 months	0.7856	(0.1389)	0.7117*	(0.1255)	0.8878	(0.0745)	0.8462 **	(0.0714)
1-2 years	0.8122	(0.1449)	0.7691	(0.1378)	0.8930	(0.0744)	0.8723	(0.0727)
2-3 years	0.8977	(0.1490)	0.8996	(0.1495)	0.9665	(0.0737)	0.9552	(0.0746)
> 3 years	0.7979	(0.1412)	0.7998	(0.1376)	0.9006	(0.0769)	0.8991	(0.0769)
risk attitude (career domain)								
score $< \mu - \sigma$	0.9714	(0.1396)	1.0244	(0.1483)	0.9965	(0.0648)	1.0157	(0.0667)
score $> \mu + \sigma$	0.8739	(0.1083)	0.9085	(0.1086)	0.9369	(0.0523)	0.9557	(0.0528)
patience								
score $< \mu - \sigma$	0.6266***	(0.0807)	0.6347***	(0.0816)	0.7968 ***	(0.0501)	0.8030 ***	(0.0510)
score $> \mu + \sigma$	1.2249	(0.1631)	1.1865	(0.1548)	1.1054 *	(0.0645)	1.0918	(0.0631)
extraversion								
score $< \mu - \sigma$	0.6184***	(0.0893)	0.6144***	(0.0873)	0.8002 ***	(0.0568)	0.7888 ***	(0.0563)
score $> \mu + \sigma$	1.0880	(0.1350)	1.0671	(0.1307)	1.0399	(0.0575)	1.0308	(0.0568)
neuroticism								
score $< \mu - \sigma$	0.8508	(0.1288)	0.8652	(0.1275)	0.9165	(0.0656)	0.9289	(0.0660)
score $> \mu + \sigma$	1.1025	(0.1577)	1.1306	(0.1601)	1.0488	(0.0652)	1.0643	(0.0657)
openness								
score $< \mu - \sigma$	0.9604	(0.1203)	1.0002	(0.1241)	0.9787	(0.0556)	0.9943	(0.0567)
score $> \mu + \sigma$	1.0762	(0.1432)	0.9377	(0.1225)	1.0274	(0.0613)	0.9686	(0.0574)
conscientiousness								
score $< \mu - \sigma$	0.9772	(0.1226)	0.9807	(0.1224)	0.9828	(0.0556)	0.9843	(0.0561)
score $> \mu + \sigma$	0.8406	(0.1076)	0.8174	(0.1034)	0.9175	(0.0539)	0.9094	(0.0533)
agreeableness								
score $< \mu - \sigma$	0.9862	(0.1230)	0.9386	(0.1160)	0.9904	(0.0564)	0.9672	(0.0552)
score $> \mu + \sigma$	0.9012	(0.1174)	0.9096	(0.1180)	0.9583	(0.0565)	0.9573	(0.0567)
local conditions at origin (district)								
GDP growth	1.0107	(0.0082)			1.0058	(0.0038)		
unemployment growth	1.1556***	(0.0605)			1.0703 ***	(0.0268)		
population density (log)	0.8090***	(0.0438)			0.9113 ***	(0.0233)		
recreational area (per capita, log)	0.5399***	(0.0691)			0.7511 ***	(0.0445)		
constant					✓		✓	
cut points ($\kappa_1, \kappa_2, \kappa_3$)	✓		✓					
observations	1717		1717		1717		1717	
log likelihood	-1911.49		-1947.14		-2149.57		-2200.78	
df	28		24		28		24	
LR χ^2(df)	137.31		71.42		132.44		70.62	
prob > χ^2	0.0000		0.0000		0.0000		0.0000	
pseudo R-squared	0.0357		0.0174					
Brant test (χ^2 / df / P>χ^2)	60.55 / 56 / 0.315		51.04 / 48 / 0.355					
Wolfe-Gould test (χ^2 / df / P>χ^2)	54.35 / 56 / 0.207		52.07 / 48 / 0.319					

*** p<0.01, ** p<0.05, * p<0.1

Some other findings, of slightly less robust nature, deserve some mentioning: local conditions at individuals' origins exhibit some explanatory power in the initial choice set's scope approach as well. The environment with which one is confronted around graduation from school might have some impact on the decision-making process. If, for instance, employment perspectives are poor, investing in human capital - and thereby acquiring the skills to enter later into the white-collar labour market - might become more attractive. This explains the positive relationship between unemployment growth and a larger initial choice set, increasing admission likelihood.

Population density and recreational area at the district of origin are negatively associated to the choice set's size. A plausible explanation is a certain preference for the current centre of one's life, being characterised by a certain degree of urbanisation and recreational value. If staying in such an environment yields non-monetary returns, increasing the choice set by applying to a larger number of distant universities would not be optimal. At the same time, even in larger cities the number of potential institutions offering the desired study programme is limited.

Furthermore, GDP growth is positively related to the occurrence of larger choice sets, though typically only significant at the 10 % significance level. A higher GDP growth, in turn, is indicative of increasing household wealth. Improving economic circumstances might eventually enable some individuals to apply at institutions located in destinations with higher price levels, which are on average inaccessible to individuals from less affluent origins. This expands the potential set of destinations for persons from economically prospering districts, translating into larger choice sets.

On the level of individual traits, only weak evidence exists in favour of a direct link between a higher willingness to take risks and a diminishing choice set's scope, including geographically distinct locations (Table A3.3). Relationship status, in contrast, proves to be more insightful: compared to individuals not in a relationship, those in a relationship of six to twelve months or two years feature distinctly smaller choice sets. The benefits of increasing the choice set, requiring possibly applications at distant institutions, might not compensate adequately if the partner lives in the district of origin.

Those aspects, which are enhancing the value of staying at one specific familiar location, especially seem to confine the choice set's scope. Their impact should become more visible in the subsequent choice set's components approach, explicitly integrating the geographic dimension.

3.4.3 The initial choice set's components

Initial choice sets will not only vary with respect to their size, but also regarding their components: depending on individual preferences and circumstances, chosen alternatives should display some common features. In the context of choosing a study location, potentially resulting in a mobility event, a relevant criterion for an alternative's inclusion into the initial choice set is distance. Moreover, contingent upon individual traits and preferences, observed components should be optimally chosen.

Establishing a link between individual traits and those optimally chosen components, evaluated in the distance dimension, informs about an individual's fundamental willingness to migrate at the initial decision stage. Acknowledging the existence of revealed alternatives, the initial choice set's components approach provides insights into a basic mobility inclination, undistorted by subsequent external admission processes. Such downstream acceptance processes in the sense of a potential supply side restriction, possibly eliminating most preferred alternatives, may introduce bias to the estimated relationship between individual traits and observed outcomes in a migration context.

To evaluate the choice set's components in the distance domain, the baseline measure is defined as the distance between an individual's origin (where someone graduated from school) and a selected alternative. It is calculated as the distance between the two corresponding postal code area's centroids, yielding an average distance between the two small-scale areas. This simple geographic distance measure, indicating a basic inclination towards mobility for educational purposes, has a clear drawback: a higher value does not necessarily imply that the respective individual is fundamentally more willing to move farther than another person with a somehow lower value. In fact, the higher value might just be an artefact if someone lived in a more rural area, and hence the closest university was more distant.

To mitigate the ramifications of this issue, the concept of 'excess mobility' is introduced: it is defined as the difference between the distance to a potential university location and the distance to the nearest university (or university of applied sciences) offering an economics bachelor programme.[32] Referring to Figure 3.3 (left panel), the excess distance in case of the most preferred alternative would be the difference between the distance from 'origin' to the location labelled '1' less the distance from 'origin' to location '2'.

Three distinct measures of excess mobility will be investigated, all on the kilometre scale. The first is the minimum excess distance (d^{min}), referring to the closest alternative in the initial choice set. Its counterpart is the maximum excess distance (d^{max}), accounting for the most distant selected alternative. The third measure is the average excess distance (d^{avg}) of all stated alternatives in the initial choice set. This measure takes into account the geographic dispersion of observed components in the choice set and reflects by how much a person was willing to move beyond the closest possible destination on average.

A fourth measure relaxes the assumption of disclosed absolute distances, and introduces relative distances. Individuals may not exactly know the distance between a larger number of potential destinations and their origin, but may have formed an educated guess regarding which locations are closer and which are distant. Such relative distances are captured by a rank measure, representing an alternative's relative position amongst all potential 164 alternatives in the destination space. For the

[32] Alternative specifications were based on excess mobility in relation to universities, yet the results were almost identical.

sake of brevity, only results for average rank positions of alternatives (r_d^{avg}) in the initial choice set are reported.

On average, the closest alternative in the initial choice set was 42.76 kilometres farther away than the nearest potential study location (Table 3.4). However, at least one fourth selected the closest possible alternative into the initial choice set.[33] All three excess mobility measures and the rank-based measure are distinctly right-skewed, indicating a strong preference for closer alternatives right from the start when students formed their initial choice set.

Table 3.4: Choice sets' components – potential excess mobility and rank based mobility

	mean	std. dev.	p10	p25	p50	p75	p90
d^{min}	42.76	70.92	0.0	0.0	13.6	53.8	126.0
d^{avg}	100.42	94.58	0.0	28.1	73.7	147.3	230.4
d^{max}	169.50	150.73	0.0	46.8	122.0	267.2	399.1
r_d^{avg}	25.88	27.89	1.0	5.5	15.3	37.8	66.8

Note: The sample size is in all four cases 1714 individuals. Columns labelled 'p' document corresponding percentile thresholds.

The first analytical step in investigating the initial inclination towards mobility is a linear estimation of potential excess mobility

$$d^j = X'\beta + \varepsilon.$$

Model specifications are identical to those in the scope approach. This also includes an IV estimation to account for the potential endogeneity of some regressors (proximity to reference persons and adaptability). Though the dependent variable is highly right skewed, it is not log-transformed, since estimating the conditional mean function $E\left[\ln\left(d^j \middle| X\right)\right] = X'\beta$ was only possible for $d^j > 0$. This, however, would result in the loss of a substantial number of observations.

A strategy to account for the dependent variable's skewedness and $d^j = 0$ is the estimation of a generalised linear model (GLM). The selected gamma model with log-link function relies then on the natural logarithm of the expected outcome

$$\ln\left(E[d^j|X]\right) = X'\beta.$$

This specification furthermore assumes the outcome variable d^j to follow a gamma distribution $\Gamma(a, b)$, with shape parameter $a \leq 1$ and a scale parameter b.[34] Such a specification is suitable to deliver estimates in a model of continuous positive distances, which do not suffer from an upward bias observed in a log-transformed OLS model.

In contrast to the scope approach, there is substantial evidence in favour of the two critical regressors (importance of proximity to reference persons and adaptability) actually being endogenous (Table 3.5). First stage results are virtually identical to the scope approach,[35] lending support to a channel on how previous mobility experiences may affect perceived psychic costs in

[33] This is indicated by $d^{min} = 0$ for the 25th percentile.

[34] The shape parameter's definition corresponds to a non-symmetric distribution, as observed in the data. The scale parameter reflects the dispersion above zero.

[35] Minor changes in some decimal places originate solely from the slightly different sample (1714 instead of 1717 individuals). As in the scope approach, comparing F-statistics from a test on joint significance of the instruments to the critical Stock and Yogo (2005) values indicates that the instruments pass the weak instrument test.

subsequent mobility-related decision scenarios: on the one hand via a lowered importance of proximity to reference persons, and on the other hand via an increased adjustment capability.

Table 3.5: Choice set's components – potential excess mobility (OLS and IV)

dependent variable	d_{i,C_0}^{avg}									
estimation method	OLS		OLS		IV (2nd stage)		OLS		IV (2nd stage)	
	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.
gender (female)	1.149	(4.868)	4.458	(4.761)	14.507	(14.479)	2.760	(4.731)	10.046	(15.954)
age	3.948**	(1.793)	3.769**	(1.800)	1.068	(3.984)	4.279**	(1.797)	1.671	(4.045)
academic household	21.245***	(4.758)	17.411***	(4.646)	-6.606	(12.290)	16.845***	(4.645)	-7.392	(12.816)
uec grade	-4.170	(4.704)	-7.714*	(4.583)	-36.621***	(13.157)	-10.031**	(4.387)	-42.911***	(14.422)
vocational training	-13.122	(8.752)	-9.184	(8.660)	16.740	(19.499)	-8.892	(8.559)	17.577	(20.211)
partnership										
< 6 months	-4.533	(9.052)	-1.940	(8.740)	1.517	(20.566)	-1.890	(8.693)	-1.689	(21.973)
6-12 months	-19.470**	(7.926)	-15.571**	(7.837)	-6.856	(22.247)	-17.495**	(7.870)	-13.282	(23.896)
1-2 years	-21.721***	(7.355)	-14.594**	(7.428)	29.738	(21.636)	-15.208**	(7.463)	28.099	(22.449)
2-3 years	-15.927**	(7.987)	-11.688	(7.889)	17.066	(19.147)	-11.645	(7.998)	17.629	(20.015)
> 3 years	-32.705***	(8.098)	-29.334***	(7.815)	-13.258	(18.001)	-29.056***	(7.860)	-14.009	(19.052)
risk attitude (career domain)										
score $< \mu - \sigma$	-14.375**	(6.384)	-11.102*	(6.163)	11.176	(15.462)	-10.346*	(6.129)	13.331	(16.239)
score $> \mu + \sigma$	4.348	(5.802)	-0.293	(5.752)	-28.032*	(15.037)	0.140	(5.789)	-27.146*	(15.784)
patience										
score $< \mu - \sigma$	-14.756**	(5.847)	-13.962**	(5.695)	-9.756	(11.722)	-13.988**	(5.751)	-9.470	(12.248)
score $> \mu + \sigma$	15.848**	(7.092)	9.115	(6.973)	-44.928**	(21.824)	8.401	(6.949)	-47.914**	(22.914)
extraversion										
score $< \mu - \sigma$	-21.020***	(6.495)	-10.548	(6.645)	85.295**	(37.770)	-12.029*	(6.674)	89.833**	(40.300)
score $> \mu + \sigma$	-1.881	(6.049)	-6.080	(5.907)	-52.378**	(22.379)	-6.203	(5.910)	-57.158**	(24.482)
neuroticism										
score $< \mu - \sigma$	-0.230	(7.430)	-4.650	(7.300)	-60.017**	(28.324)	-4.636	(7.307)	-64.610**	(30.184)
score $> \mu + \sigma$	5.323	(6.387)	9.673	(6.175)	53.138**	(21.746)	10.632*	(6.198)	57.570**	(23.472)
openness										
score $< \mu - \sigma$	-9.434*	(5.338)	-5.580	(5.235)	20.364	(13.580)	-4.687	(5.236)	21.697	(14.187)
score $> \mu + \sigma$	14.120**	(6.660)	11.395*	(6.524)	-9.609	(14.464)	8.728	(6.422)	-15.453	(15.362)
conscientiousness										
score $< \mu - \sigma$	-0.976	(5.731)	-1.753	(5.575)	-0.027	(12.189)	-1.570	(5.622)	1.670	(12.850)
score $> \mu + \sigma$	-8.711	(5.970)	-9.957*	(5.997)	-28.053*	(15.943)	-10.258*	(5.996)	-30.426*	(16.982)
agreeableness										
score $< \mu - \sigma$	-6.038	(5.546)	-8.507	(5.499)	-14.071	(14.921)	-9.612*	(5.539)	-14.081	(15.614)
score $> \mu + \sigma$	-5.434	(6.078)	-5.208	(5.910)	-13.653	(14.266)	-5.152	(5.957)	-15.767	(15.307)
x_1^{endog}: imp. of prox. (family)			-9.641***	(1.529)	-43.939	(29.110)	-9.787***	(1.538)	-39.366	(31.577)
x_2^{endog}: adaptability			8.208***	(1.603)	103.120**	(40.874)	7.967***	(1.605)	111.802**	(44.734)
origin controls	✓		✓		✓					
constant	✓		✓		✓		✓		✓	
observations	1714		1714		1714		1714		1714	
df	28		30		30		26		26	
F / Wald χ^2	4.82		6.71		47.99		6.89		38.46	
prob > F / prob > χ^2	0.0000		0.0000		0.0199		0.0000		0.0548	
pseudo R^2 / adjusted R^2	0.0523		0.1005				0.0922			
exogeneity test										
Wooldridge (1995) score test					36.44 (p=0.0000)				37.39 (p=0.0000)	
regression based test					18.39 (p=0.0000)				18.93 (p=0.0000)	
1st stage: x_1^{endog}										
F(model)					6.48 (p=0.0000)				7.13 (p=0.0000)	
z_1: res. move during school					-0.3689 ***	(0.0979)			-0.3588 ***	(0.0974)
z_2: exchange participation					-0.1238	(0.0817)			-0.1286	(0.0815)
F(instruments)					8.44 (p=0.0002)				8.24 (p=0.0003)	
1st stage: x_2^{endog}										
F(model)					13.54 (p=0.0000)				15.08 (p=0.0000)	
z_1: res. move during school					0.0005	(0.0857)			0.0081	(0.0857)
z_2: exchange participation					0.2469 ***	(0.0744)			0.2385 ***	(0.0743)
F(instruments)					5.56 (p=0.0039)				5.20 (p=0.0056)	
weak instrument test										
F^{crit} $(\alpha = 0.10)$					7.03				7.03	
F^{crit} $(\alpha = 0.15)$					4.58				4.58	
F^{crit} $(\alpha = 0.20)$					3.95				3.95	

*** p<0.01, ** p<0.05, * p<0.1

Note: The two potentially endogenous variables (importance of proximity to family and adaptability to new circumstance) enter the specifications as quasi continuous variables (on a scale from 1 to 7). This modification is implemented with regard to the first stage estimations. F^{crit}report the critical values of Stock and Yogo's (2005) weak instrument t assuming i.i.d. error structure.

Second stage results indicate, however, that only the latter might be relevant. The lower the instrumented degree of adaptability, the more clustered are the selected alternatives around the origin. In addition, second stage results also portend a preference of low performing pupils for choosing closer alternatives: students with a one grade worse university entrance certificate select alternatives that are on average 36.6 to 42.9 kilometres closer to their origin.

In addition, those individuals most willing to take risks are restricting their initial choice set to consist of closer alternatives. Considering that these applicants do in fact limit their overall access to a broader spectrum of institutions of higher education, such patterns related to risk attitude become reasonable. A remaining issue is the overall model fit in case of the IV estimations. Though the specifications can address some potential endogeneity in factors related to psychic costs, relatively small Wald test statistics for the second stage (p-values of 0.0199 and 0.0548) indicate a potential lack of overall explanatory power. Given the dependent variables' highly right-skewed distribution, such small a model fit is a likely outcome.

In order to overcome this limitation, Table 3.6 reports average marginal effects from the above mentioned GLM estimation. The model specification corresponds to the one in the first column in Table 3.5, thus to a specification without the two endogenous variables.[36]

Although the underlying concepts vary, results are highly comparable across the varying definitions of the dependent variable, both regarding magnitude and significance. Accounting for the skewed nature of the dependent variable, several robust findings emerge.

Individuals from an academic household, select on average potential destinations into their initial choice set that are 20.5 kilometres farther away than those from a non-academic background. This points to the existence of an intergenerational transmission of mobility preferences. Social life, i.e., being in a relationship, seems to affect the formation of the initial choice set as well. Aside from those shortly in a relationship, being in a relationship makes the preselected alternatives more clustered around the origin. This just confirms that long-term relationships might indeed hamper mobility of only one partner, respectively lead to tied-stayers (cf. Mincer, 1978) with an implicitly restricted access to higher education. Such restrictions regarding enrolment alternatives into tertiary education, hence bearing the potential to affect the human capital formation adversely, might also have repercussions on subsequent post-graduation earnings paths.

In line with hypotheses on human capital investment, least patient individuals applied on average (referring to d_{i,C_0}^{avg}) at locations 16.4 kilometres closer to their origin. A similar pattern can be detected for least extraverted individuals or those least open to experience, the latter effects being typically only half the size. These two traits appear to be related to how individuals perceive psychic costs of mobility – not only do some individuals eventually choose closer alternatives, they

[36] Raw coefficients are reported in Table A3.6 in the appendix. Based on a link test, the discussed specifications do not include origin controls.

considered only potential destinations in closer proximity to their current living environment right from the start.

As in the scope approach, the evidence for a prominent role of risk attitude during the formation of the initial choice set is limited. Least risk-prone individuals tend to select a closest alternative (d_{i,C_0}^{min}) that is 10.5 kilometres nearer compared to the reference group, formed by individuals of average willingness to take risk. On average, their most preferred alternatives in the initial choice set are 13.8 kilometres closer to their origin.

Table 3.6: Choice set's components – average marginal effects

dependent variable	d_{i,C_0}^{min}		d_{i,C_0}^{avg}		d_{i,C_0}^{max}		r_{d,i,C_0}^{avg}	
estimation method	Γ, log-link		Γ, log-link		Γ, log-link		Γ, log-link	
	AME	s.e.	AME	s.e.	AME	s.e.	AME	s.e.
gender (female)	0.8601	(3.6229)	-1.7273	(4.8700)	-4.4568	(8.0024)	-1.3412	(1.4521)
age	4.0914***	(1.3253)	4.1766**	(1.8107)	2.9189	(2.9258)	0.9840*	(0.5402)
academic household	6.9917*	(3.5910)	20.5438***	(4.7590)	37.0998***	(7.6120)	5.6413***	(1.4059)
uec grade	1.4315	(3.2196)	-5.1830	(4.2231)	-14.6298**	(6.7353)	-2.7134**	(1.2608)
vocational training	-11.8111**	(5.2232)	-13.3834*	(7.9510)	-8.2074	(13.8485)	-4.8333**	(2.2793)
partnership								
< 6 months	4.1830	(6.6677)	-1.0237	(9.1315)	-1.6672	(14.5714)	-0.7729	(2.6406)
6-12 months	-10.6084*	(5.5893)	-18.9172**	(8.3334)	-27.6453*	(14.1786)	-4.7062*	(2.6094)
1-2 years	-1.9407	(5.8752)	-21.3984***	(7.2287)	-38.5916***	(11.4498)	-6.2108***	(2.1397)
2-3 years	-7.4783	(5.8718)	-17.8535**	(7.9902)	-28.6185**	(12.4938)	-6.5060***	(2.1893)
> 3 years	-13.3133**	(5.4834)	-33.0298***	(7.8107)	-53.2971***	(13.2006)	-8.9455***	(2.3425)
risk attitude (career domain)								
score $< \mu - \sigma$	-10.5157**	(4.3960)	-13.8311**	(6.7125)	-13.4694	(11.1355)	-3.2107	(2.0389)
score $> \mu + \sigma$	4.9884	(4.5372)	4.8142	(5.6465)	10.1732	(8.9782)	1.3160	(1.6920)
patience								
score $< \mu - \sigma$	1.2761	(4.6474)	-16.3669***	(5.8037)	-36.4541***	(8.9562)	-4.2769**	(1.7228)
score $> \mu + \sigma$	6.6378	(5.0064)	15.7202**	(7.0422)	25.4126**	(11.1420)	5.0389**	(2.0770)
extraversion								
score $< \mu - \sigma$	-10.1447**	(4.5885)	-22.4361***	(6.4007)	-36.4696***	(10.4541)	-5.8311***	(1.9473)
score $> \mu + \sigma$	2.7971	(4.5954)	1.3506	(6.1773)	0.1101	(9.5550)	0.1055	(1.7950)
neuroticism								
score $< \mu - \sigma$	2.1145	(5.5139)	2.0875	(7.3274)	-0.3355	(11.2938)	0.0996	(2.1360)
score $> \mu + \sigma$	4.9106	(5.1794)	6.8227	(6.9592)	7.9829	(11.0581)	2.2010	(2.1187)
openness								
score $< \mu - \sigma$	-8.0848**	(3.6616)	-10.7644**	(5.2438)	-15.7635*	(8.9471)	-3.6385**	(1.5426)
score $> \mu + \sigma$	3.2691	(4.7926)	9.4261	(6.6993)	17.5075	(10.7821)	1.8823	(2.0043)
conscientiousness								
score $< \mu - \sigma$	-2.0667	(4.3274)	0.9482	(5.9664)	3.8884	(9.8332)	-0.0715	(1.7846)
score $> \mu + \sigma$	-9.0156**	(4.1343)	-9.7699*	(5.8804)	-13.6331	(9.5210)	-3.1152*	(1.7138)
agreeableness								
score $< \mu - \sigma$	-5.1073	(4.2424)	-6.5983	(5.7975)	-7.5946	(9.4467)	-1.0605	(1.7865)
score $> \mu + \sigma$	-7.7450*	(4.1753)	-5.9363	(6.0763)	-1.8982	(10.0972)	-2.0955	(1.7534)
observations	1714		1714		1714		1714	
log likelihood	-8078.01		-9568.16		-10459.99		-7233.39	
deviance	1549.73		1240.93		1236.63		2283.23	
rank (k)	25		25		25		25	
AIC	9.4551		11.1939		12.2345		8.4695	
BIC	-11027.55		-11336.36		-11340.65		-10294.05	

*** p<0.01, ** p<0.05, * p<0.1

Note: The diagnostic section is taken from Table A3.6 in the appendix. AMEs for the first three specifications correspond to kilometre changes. For the rank distance measure, the AMEs inform about changes in the average rank position of alternatives in the initial choice set.

Typically, factors relevant for explaining the size of individuals' initial choice sets also display distinct explanatory power in the components approach: if the sign of corresponding coefficients is consistent, their statistical significance in the components approach is usually more pronounced. Moreover, the socio-demographic background becomes more important when it comes to selecting potential alternatives. The linkage between relationship status and the clustering of preselected alternatives in a relatively close proximity is especially salient. In a similar fashion, perceived psychic costs are influenced by the personality traits extraversion and openness. Empirical evidence suggests that individuals, who score low in these two traits, already anticipate during the initial decision-making process that they might have a harder time handling new experiences and reconnecting if they leave their familiar environment.

The next chapter investigates the extent to which these considerations uphold when it comes to the final decision for one location, after the potential restriction of the initial choice set by the admission process at a chosen study location.

3.5 Observed mobility choices

After prospective students revealed their basic preferences regarding a specific study programme and location during the formation of the initial choice set, their final choice set is then determined by the institutions' admission process. Depending on universities' selection criteria, the size of the final choice set C_1 varies between one and the maximum scope of the initial choice set.[37]

If the final choice set is larger than one, additional information can then be obtained from the location choice: it is now possible to identify a decision-maker's willingness to migrate based on whether he or she chooses an alternative nearby or farther away (for example see Figure 3.3, right panel).

3.5.1 Migratory preferences in the presence of alternatives

To assess possible factors influencing mobility-related choices of students in a more robust way, individually displayed geographic mobility is evaluated based on three alternative dependent variables. The first one is constructed as binary variable, indicating whether someone chose the closest alternative over the most preferred alternative with admission in the subset of size $n_{i,C_1}^{*} = 2$. Referring to the right panel in Figure 3.3, the dependent variable $u_i | n_{i,C_1}^{*} = 2$ is coded as one, if the most preferred location '1' is the closer alternative, and zero if the finally chosen university 'U' is the closer alternative.[38] The second binary dependent variable ($u_i | n_{i,C_1}^{*} \in [2,4]$) accounts for all observed alternatives in the final choice set C_1 of size $n_{i,C_1}^{*} \in [2,4]$. Once again, this variable is encoded as one if the eventually chosen alternative 'U' is not the closest location and zero if it is the closest option to the previous location amongst all stated available alternatives.

More information regarding geographic mobility is contained in the third dependent variable ($r_u | n_{i,C_1}^{*} \in [2,4]$), being of ordinal nature. The three categories indicate whether someone picked the closest observed alternative in the final choice set C_1, a destination at intermediate distance or the

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[37] Principally, the choice set could also collapse to zero if all applications were rejected. As the sample under scrutiny consists of enrolled students, the final choice set's de facto minimum scope is one.

[38] $u_i | n_{i,C_1}^{L^*} = 2$ indicates whenever the chosen alternative was not the closest alternative (compared to the most preferred alternative), given the two options are geographically distinct locations. This variable mirrors the concept from the scope approach.

remotest available alternative with admission. Ultimately, this concept's categories capture a progressive degree of displayed mobility.

As in the analyses of the choice set formation, the binary variables have been investigated in a linear probability model in a first analytical step. Subsequent IV estimations (Table A3.7, in the appendix), addressing the possible endogeneity of factors impacting on perceived psychic costs (proximity to family and adaptability), signify potential endogeneity only for the decisions in the context of the complete observed final choice set ($u_i|n^*_{i,C_1} \in [2,4]$).

Table 3.7: Observed mobility – logit and ordered logit models

dependent variable	$u_i\|n^*_{i,C_1} = 2$		$u_i\|n^{L^*}_{i,C_1} = 2$		$u_i\|n^*_{i,C_1} \in [2,4]$		$r_u\|n^*_{i,C_1} \in [2,4]$	
estimation method	logit		logit		logit		ologit	
	OR	s.e.	OR	s.e.	OR	s.e.	OR	s.e.
gender (female)	1.0032	(0.1505)	0.9774	(0.1446)	1.3635**	(0.1929)	1.3439**	(0.1775)
age	0.9337	(0.0560)	0.9290	(0.0536)	0.9857	(0.0521)	0.9812	(0.0492)
academic household	0.9554	(0.1328)	0.9730	(0.1331)	1.2208	(0.1605)	1.0704	(0.1313)
uec grade	1.8299***	(0.2616)	1.6898***	(0.2353)	1.2228	(0.1595)	1.3877***	(0.1722)
vocational training	0.7035	(0.1882)	0.7374	(0.1922)	0.7147	(0.1776)	0.6173**	(0.1392)
partnership								
< 6 months	0.9377	(0.2372)	0.8894	(0.2224)	0.7150	(0.1726)	0.7725	(0.1800)
6-12 months	0.8895	(0.2271)	0.8375	(0.2119)	0.6840	(0.1621)	0.6778*	(0.1529)
1-2 years	0.6984	(0.1782)	0.8756	(0.2141)	0.7772	(0.1767)	0.8761	(0.2025)
2-3 years	0.7238	(0.1870)	0.6620	(0.1699)	0.7149	(0.1707)	0.6986	(0.1554)
> 3 years	1.3809	(0.3729)	1.4869	(0.3904)	1.3621	(0.3447)	1.3789	(0.3096)
risk attitude (career domain)								
score $< \mu - \sigma$	0.7350	(0.1694)	0.6870*	(0.1545)	0.7219	(0.1478)	0.7035*	(0.1348)
score $> \mu + \sigma$	1.1570	(0.1860)	1.1265	(0.1789)	1.2061	(0.1888)	1.0976	(0.1536)
patience								
score $< \mu - \sigma$	1.1196	(0.2215)	1.0239	(0.1999)	0.7799	(0.1454)	0.8085	(0.1506)
score $> \mu + \sigma$	1.0991	(0.2012)	1.1379	(0.2039)	1.1896	(0.2114)	1.1490	(0.1802)
extraversion								
score $< \mu - \sigma$	0.6061**	(0.1390)	0.5789**	(0.1319)	0.7560	(0.1548)	0.7455	(0.1425)
score $> \mu + \sigma$	1.0195	(0.1769)	1.0689	(0.1815)	1.1318	(0.1865)	1.1651	(0.1787)
neuroticism								
score $< \mu - \sigma$	0.8613	(0.1902)	0.9240	(0.1962)	0.9946	(0.2007)	1.0100	(0.1971)
score $> \mu + \sigma$	0.9959	(0.1933)	0.9262	(0.1777)	0.8475	(0.1551)	0.7434*	(0.1169)
openness								
score $< \mu - \sigma$	0.8660	(0.1553)	0.9091	(0.1583)	1.2109	(0.1986)	1.1286	(0.1717)
score $> \mu + \sigma$	1.1381	(0.2078)	1.1273	(0.2036)	1.1996	(0.2084)	1.1387	(0.1806)
conscientiousness								
score $< \mu - \sigma$	1.0662	(0.1919)	1.0174	(0.1798)	1.0212	(0.1729)	0.9794	(0.1609)
score $> \mu + \sigma$	1.0519	(0.1971)	0.9996	(0.1833)	1.0375	(0.1822)	0.8997	(0.1367)
agreeableness								
score $< \mu - \sigma$	0.6563**	(0.1217)	0.6651**	(0.1193)	0.9720	(0.1613)	0.9820	(0.1505)
score $> \mu + \sigma$	1.4568**	(0.2665)	1.4255**	(0.2578)	1.3979*	(0.2514)	1.4132**	(0.2352)
distance to closest alternative	✓		✓		✓		✓	
constant	✓		✓		✓			
cut points (κ_1, κ_2)							✓	
observations	1053		1053		1053		1053	
log likelihood	-648.71		-665.43		-710.26		-1077.43	
df	25		25		25		25	
LR χ^2(df)	47.96		46.61		33.76		42.73	
prob > χ^2	0.0038		0.0054		0.1132		0.0150	
pseudo R-squared	0.0399		0.0368		0.0250		0.0203	
Brant test (χ^2 / df / P>χ^2)							43.28 / 25 / 0.013	
Wolfe-Gould test (χ^2 / df / P>χ^2)							41.52 / 25 / 0.020	

*** p<0.01, ** p<0.05, * p<0.1

Note: Inference is based on robust standard errors. A model comparison is reported in Table A3.8. The sample consists of those individuals having a final choice set C_1 containing at least two alternatives with admission.

In either case, a smaller sample, consisting only of those individuals with at least one additional alternative, affected the reliability of the first stages: first stage F-statistics are much smaller, and although the instruments maintain their individual explanatory power in the first stages, they no longer pass Stock and Yogo's (2005) weak instrument test at reasonable levels. This finds expression in second stages displaying a scant model fit at best.

Focusing on logit specifications, not comprising the two critical regressors, provides informative results regarding mobility outcomes in the presence of observed alternatives (Table 3.7): in reference to the most preferred alternative, least extraverted individuals have odds of selecting the more distant alternative that are only 0.6 times the odds of the reference group.

In contrast, this result vanishes by enclosing the full final choice set of size $n^*_{i,C_1} \in [2{,}4]$ into the analyses. Accounting for all actually observed alternatives, which mimics the more complex decision scenario individuals face in reality, extraversion loses its predictive power. In this scenario, women display distinctly higher odds than men to not opt for the closest available alternative.

Conditioning on geographically distinct locations ($u_i|n^{L^*}_{i,C_1} = 2$) reveals that most risk-averse persons have similarly decreased odds (0.687), as compared to the average risk-type individuals. This finding is reproduced in the ordered logit specification: once again, individuals least willing to take risk feature odds of choosing an alternative at intermediate or maximum distance that are 0.7 times smaller than the reference group. A similar decrease in odds is recognisable for those individuals scoring highest in the Big-Five trait neuroticism.

One drawback in case of the analyses of ranked (ordered) mobility outcomes is a potential violation of the proportional odds assumption, as suggested by the test statistics of the Brant and Wolfe-Gould tests. The robustness of the basic findings (Table A3.9) is supported upon the application of a partial proportional odds model (Williams, 2006), which allows some coefficients to differ across ordered outcome groups. Beyond that, it lends support to the hypothesis that individuals of differing personality types exhibit varying degrees of sensitivity with respect to distance: the odds of a most neurotic individual choosing an alternative at intermediate distance over one at minimum distance are below unity, but not significant. Yet, these odds are approximately 0.5 times smaller, and significant, when it comes to the choice between an alternative at maximum distance and one at intermediate (or minimum) distance. Relaxing the proportional odds assumption, most conscientious individuals display a decision-making pattern comparable to those scoring highest in the Big-Five trait neuroticism.

A robust finding is the relationship between the Big-Five trait agreeableness and observed mobility outcomes. Irrespective of whether a subset of the final choice set ($u_i|n^*_{i,C_1} = 2$, $u_i|n^{L^*}_{i,C_1} = 2$) or the complete admission set ($u_i|n^*_{i,C_1} \in [2{,}4]$, $r_u|n^*_{i,C_1} \in [2{,}4]$) is taken into account, odds ratios are numerically invariant and significantly different from unity: most agreeable individuals display odds of selecting the more distant alternative over other most preferred, but nearer locations that are 1.4 times higher than in the reference group. Since an important dimension of the trait agreeableness is trust in other individuals,[39] this finding is directly interpretable: a higher willingness to trust in others may lower the expected transaction costs associated to interactions with unknown individuals in an unfamiliar environment. This, in turn, is likely to notably mitigate the perceived costs of mobility.

3.5.2 On the results' sensitivity regarding the distance concept

The relevance of the dimension 'distance' in migration processes has been stressed several times. Its significance was underpinned in the analysis concerning the generation of the initial choice set – specific types of individuals already refrained in the first step from considering more remote potential destinations. Others not only displayed a strong inclination regarding more pronounced geographic mobility but eventually opted for the more distant alternatives.

In the models above, distance was identified as the simple geographic distance between the centroids of the two postal code areas, origin and (potential) destination. Obviously, one cannot always travel as a bird flies, and therefore this distance measure might be overly simplistic and misguiding. If individuals explicitly integrated distance into their decision-making to account for distance related costs, they could directly use information from the known map and routing services: kilometres to travel or required travel time. In order to test the results' sensitivity related to the used distance concept, I re-estimated some benchmark models for observed mobility outcomes, now accounting for these two alternative distance measures.

Both measures originate from the 'reachability model', developed by the Federal Institute for Research on Building, Urban Affairs and Spatial Development (BBSR). The underlying model provides information on the accessibility of over 11000 municipal or traffic cells within Germany. A first matrix contains road distances between these reference points, while a second matrix comprises travel time on roads. Derived travel times are based on various speed profiles, according to the road type, also integrating traffic flow features between two traffic cells. For the sake of the subsequent robustness check, these traffic cells were matched to the corresponding postal code areas.

Table A3.10 (in the appendix) reports the results for the binary dependent variables $u_i|n^*_{i,C_1} = 2$, based on the same model specifications documented in Table 3.7 and Table A3.8.

Calculated odds ratios are numerically stable across the alternative specifications. This holds not only for a comparison between the geographic distance concept on the one hand, and road distance or travel time on the other, but also regarding a model comparison building upon the alternative concepts. Analytical results in the examination of whether someone chooses the closest location over the most preferred reported alternative are not driven by the underlying distance concept. The sole noteworthy difference is a more frequent and robust occurrence of significantly smaller odds ratios for individuals in a relationship of intermediate duration in case of the distance concept travel

[39] The second dimension of the Big-Five trait agreeableness in the implemented short inventory is the tendency to find fault with others (Rammstedt and John, 2007)

time. Individuals in such a relationship might put a higher emphasis on spending time with their partner, who possibly stays at the current location, thus value the time itself more.

Taken altogether, results are remarkably robust towards the investigated distance concept. This holds albeit there are in principle plausible arguments why simple geographic distance might be an insufficient proxy for covered distance or required travel time, and thus also related costs in the context of mobility.

Two main reasons for this robustness could be invoked: first, in the case of Germany, offering a well-developed traffic system, the correlation between geographic distance and the two alternative distance concepts is extremely high. The utility maximising outcome in a comparison of destinations does not change if an individual evaluates costs of mobility based on kilometres (to drive) or time spent travelling. The second argument is that car driving might not be the most relevant travel mode for young adults, such as first semester students, around the age of 20. This could be attributed to infrequent car ownership or a general preference for other, less expensive means of transportation, i.e., public transport.

Given these findings, evaluating internal migration of individuals based on simple geographic distances between centroids of areas sufficiently small proves to be a reliable approach.

3.6 Discussion and conclusion

This study investigates mobility inclination and observed geographic mobility of prospective high-skilled labour force participants. Beginning students were observed at a transitional point in early adulthood, when they - mostly for the first time - made an autonomous mobility-related decision: they chose a study location amongst a variety of potential alternatives.

In contrast to other studies, most preferred considered alternatives during the decision-making process are known. This allows an examination of how individuals, in a first step, generate their initial choice set. It can vary regarding its scope, since some individuals might consider more potential alternatives than others. At the same time, this set's components are likely to reflect the heterogeneity of the decision-makers: an individual's preferred alternatives will display some common features, such as distance to a decision-maker's current location, which introduces the migration aspect into this choice.

Least patient individuals are found to form distinctly smaller initial choice sets, as do those least extraverted. Since a larger choice set is associated with a higher overall admission likelihood, these findings correspond to lower expected returns to tertiary education for these individuals. Similar results emerge for older ages and individuals with weaker scholastic performance or individuals in a relationship of intermediate duration.

Regarding the selected alternatives in the initial choice set, and thus already at the consideration stage, being in a relationship restricts the set of study locations to closer alternatives. Consistent with results in the scope approach, least extraverted and least patient individuals select on average closer alternatives, once again limiting their overall access to institutions of higher education. Another potential impediment, increasing perceived psychic costs, is a low degree of openness since individuals least open to experience also exhibit a noteworthy preference for alternatives closer to the familiar living environment. There is also evidence correlating least pronounced willingness to take risks to an initial choice set, consisting of alternatives clustered around the origin.

Individual factors explaining the formation of the initial choice set proved to be robust with respect to an inclusion of conditions at the origin, such as measures referring to economic circumstances, urbanisation or amenities. However, these conditions display some relevance on their own: higher GDP growth, indicative of fewer financial constraints, and weaker labour market performance were associated with larger choice sets, comprising alternatives characterised by greater geographic dispersion. Negative relations between a choice set's scope or potential migratory distance on the one hand, and population density or a measure of recreational value at the origin on the other, mirror a general preference for staying closer to urbanised amenity-rich locations.

Whilst the first part of this analysis only provides answers regarding a potential inclination towards mobility – considering a location at an initial step is not necessarily identical to actually being willing to move there – the second part is dedicated to observed migration outcomes. This divergence between a basic inclination and factual behaviour can be observed in case of the trait patience: there is not one specification where patience is significantly related to eventually choosing a more distant alternative from the final choice set. Individual time preferences may be integrated into the formation of the initial choice set, yet when it comes to a final decision based on a potentially restricted choice set, its relevance seems to be superimposed by other factors.

Amongst the Big-Five personality traits, extraversion and agreeableness display explanatory power regarding observable mobility outcomes: least extraverted or agreeable individuals are less likely to select any, but the nearest alternative. There is also some evidence that most neurotic individuals perceive psychic costs to be higher, thus they exhibit a stronger preference for closer alternatives. These findings support the hypothesis that psychic costs of moving are inflated for individuals who face a harder time establishing new social ties at an unfamiliar location.

In this regard, the relevance of reference persons, such as family, or adjustment capability may constitute a further channel regarding how individual traits or preferences affect the perception of psychic costs in a migration context. This is investigated in several instrumental estimations, where previous mobility experiences act as instruments. Residential moves during childhood and youth were associated to a lower importance of proximity to family. Exchange participation during school, in turn, was related to a more pronounced adjustment capability. Therefore, earlier mobility experiences during childhood and youth, hence at a time when individuals were not autonomous but directly dependent on parental decisions, may foster individuals' mobility during adulthood.

A related policy implication refers to the possibility of strengthening individual flexibility and adjustment capability by expanding school or comparable short-term exchange programmes during adolescence. Such programmes, causing relatively little expenses or effort, can increase internal student mobility and possibly reduce overcrowding in some universities located in metropolitan areas.

As this study demonstrates, the various stages of a migration process – thinking about moving, evaluating alternatives and then selecting amongst them – are affected by personal characteristics and preferences in heterogeneous ways. Moreover, migration outcomes seem to be based on a complex decision-making process: it requires the identification of potential destinations amongst a plethora of alternatives, and then, a joint evaluation of conditions on-site and individually perceived costs or returns to mobility.

4 Counterfactual mobility: The relevance of unchosen paths and personality for the analysis of spatial choices

4.1 Introduction

How to find one's place in a world full of opportunities and alternatives? In a literal sense, this question boils down to a discrete location choice among a plethora of alternatives at different levels, such as countries, states, cities, boroughs or streets. This question is relevant for any individual, retired or working, but especially for those starting into a new stage of life, such as taking up (academic) training. Any decision in this regard involves a comparison between a current reference point and potential benefits from changing this status quo, i.e., moving to another location. Such a comparison might involve many dimensions, e.g., employment perspectives for workers, study opportunities for prospective academics, general consumption possibilities or individual social preferences. One place can be the optimal destination for one individual, but at the same time this destination could be inconceivable for another person – depending on subjectively perceived costs and returns.

There is a wide body of literature on the relevance of place-specific amenities or labour market outcomes, respectively their mutual compensating capacity, for such migration-related decisions in general (Graves and Linneman, 1979; Roback, 1982; Clark and Cosgrove, 1991; Whisler et al., 2008). Similarly, the choice of specific locations from a set of alternatives has been investigated as well, be it on the state level (Davies et al., 2001; Schündeln, 2014) or on the community level (Bayoh et al., 2006). Depending on the individual socio-demographic or socio-economic context, individuals display highly varying degrees of short and long distance migration behaviour. Aside from external factors, individual attitudes and preferences are likely to affect subjective assessments of costs and returns to mobility as well (Jokela, 2009; Frieze and Li, 2010; Jaeger et al., 2010).

A lot is known about external factors attracting individuals to specific places, or individual attributes fostering mobility on an abstract level. Surprisingly little is known about how these influential factors interact, e.g., whether risk-averse individuals shy away from moving to a location with relatively higher unemployment rates or how social preferences exactly affect perceived (psychic) costs of migration.

These interactions are the pivotal elements of this study where I demonstrate that derived elasticities of location-specific attributes in a random utility framework vary substantially with respect to heterogeneous individual characteristics, such as risk, time or social preferences. Another focus rests on heterogeneous costs of migration which may generate specific distance-related sorting patterns. Psychic costs of migration might be larger, for instance, for individuals with a higher attachment to social reference persons, and therefore they might react less sensitively to favourable conditions at a potential destination. My approach thus enables to derive choice elasticities of destination-specific features conditional on diverse personality groupings.

In order to perform this analysis, this study relies on observed location choices of individuals, just starting into a new stage of life by enrolling into institutions of tertiary education, in a high-dimensional destination space. Each of the included destinations offers a distinct basket of amenities and local conditions. The analytic framework includes both, demand and supply aspects: individuals may apply based on their preferences, yet their choices might be restricted by admission decisions – a scenario very close to matching on the labour market.

The reason to focus on students is threefold: For one, (prospectively) high-skilled workers display a high propensity of mobility (Tolbert et al., 2009; Wozniak, 2010) – thus it is more likely to observe a mobility event. At the same time, the choice of a study location is a relevant precursor of subsequent location choices (Belfield and Morris, 1999; Groen, 2004; Busch and Weigert, 2010; Buenstorf et al., 2016). Therefore it is plausible that economic conditions already matter at this stage (McHugh and Morgan, 1984; Dotti et al., 2013), since some of the decision-makers will consider their post-graduation employment perspectives as well. Ultimately, mobility for educational purposes may prove informative regarding mobility patterns of high-skilled workers. The second reason is that this sample allows narrowing down the set of potential destinations (with at least one institution of higher education), for which a wide range of location-specific indicators is available. The third and last reason is the availability of survey data, which provides information on a variety of personal characteristics and preferences on the one hand, and on the process of location choice on the other. The data does not only provide information on the eventually chosen alternative, but also on considered alternatives at various stages within the selection process, that is, all the paths that finally have not been chosen. This in turn enables to investigate the results' sensitivity regarding alternative specifications of choice sets from an empirical point of view.

To accommodate the size of the destination space and the model parameterisation, accounting for heterogeneous individuals, a conditional logit model is applied. This model might be susceptible to varying definitions of the underlying choice set, misspecification in parameters or errors. Therefore, before actually turning to the econometric analysis, I first perform a Monte-Carlo simulation study to assess the outcomes' reliability. The implemented simulation approach acknowledges and preserves destinations' real-world features, such as economic conditions, and their position in space. Simulated individuals vary with respect to their valuation of site-specific features or costs of migration, introducing heterogeneous preferences. The overall process mimics the real-world rather precisely: not only do individuals consider choice sets of varying size, but their final choice set can also be restricted by unsuccessful applications, while both aspects are related to individual characteristics. This simulation study is therefore especially insightful regarding the impact of a supply side driven restriction of choice sets on estimates.

The remainder of this study is organised as follows: Chapter 4.2 gives an introduction to the related discrete choice literature, focusing on spatial choices, estimation procedures and choice set definition. Descriptive statistics of the survey data and destination characteristics are displayed in Chapter 4.3, since these are not only relevant for the subsequent discrete choice modelling, but also serve as a benchmark for the design of the simulation study in Chapter 4.4. Estimation results from the econometric analysis are presented in Chapter 4.5, which also includes a discussion of related issues and potential remedies. Chapter 4.6 summarises this study's main insights.

4.2 Review of the related literature on discrete choices

The first subchapter gives an overview of applications of conditional logit models in the context of spatial choices of students and the general population. These choices may stretch from community to country selection. The next subchapter discusses alternative estimation methods to investigate discrete choices. The last subchapter introduces to the issue how analysts' definitions of choice sets, respectively the assumed decision-making processes, may affect estimation outcomes.

4.2.1 Conditional logit models of human migration: Spatial choices in presence of alternatives

Partitioning the mutual selection process of colleges and students into three recursively addressed stages, Kohn et al. (1976) delivered one of the first analyses of educational choices in a geographic framework accounting for heterogeneous socio-demographic backgrounds.[40] Stratifying their sample by family income, and drawing on simulated feasible choice sets, they showed that on-site residence is more likely for less financially constrained students. Extending the conditional logit model to the college choices for graduates from 1972, 1982 and 1992 among (almost) all colleges in the US, Long (2004) stressed an attenuating deterring effect of distance across all income and ability groups over time. Tuition costs affected the choice of a specific college to a lesser extent for younger cohorts, though individuals from low income backgrounds still displayed a comparable sensitivity.

Female graduates were found to be more likely to be mobile across regions (Faggian et al., 2007), since they opted more frequently into the 'option' of being a repeat-migrant, first to university and subsequently to another region. Though the authors declared this might be a strategy to compensate for lower returns in the labour market, they did not extend their conditional logit model to account for gender-specific elasticities of regional labour-market characteristics. Young Germans, between the ages 18 to 30, do apparently also select themselves into regions offering better economic perspectives or quality of life (Schneider and Kubis, 2010). In addition, university graduates also display a noticeable preference for the 'known' around labour market entry: they favour regions which are similar to their origin regarding spoken dialect or settlement type (Buenstorf et al., 2016).

[40] In fact, the assessed stages (commuting vs. living on campus, college choice given residence decision, enrolment decision) could be seen as components for a nested logit model, although they have not been treated explicitly as such.

Applying a conditional logit model to an analysis of internal migration between 48 US states, Davies et al. (2001) demonstrated the relevance of economic opportunities and distance for a location choice. They also provided information on substitutability of economic opportunities, i.e., if the ratio of unemployment rates at destination and origin were to double, an increase of around three quarter in income would be required to maintain a destination's attractiveness.[41] These findings for intra-national migration are in line with those of Geis et al. (2013) regarding destination choice of cross-border migrants, who can choose among the USA, the UK, France and Germany.

Investigating destination choices at an early consideration stage, Lovo (2014) incorporated measures of subjective well-being and corruption levels in potential destination countries. The first was found to be associated with increasing selection likelihood, the opposite held for perceived corruption. Most interestingly, counterintuitive signs or levels of significance for GDP per capita or distance vanished when destination dummies were interacted with origin-related characteristics – the latter being a proxy for the respective conditions an individual faces.

On a geographically smaller scale, Bayoh et al. (2006) scrutinised residential choices across communities in a metropolitan area. School quality and safety, both public goods, were the predominant factors influencing community choices. Incorporating an interaction of community dummies and household attributes, such as household income and number of school-age children, they also provided some guidance regarding the relevance of household specific characteristics:[42] with respect to the reference community, for instance, the likelihood of choosing a city centre residence decreases by 0.09 percentage points if household income increases by one per cent.

The attractiveness of Australian regional capital cities seems to be declining with the decision-maker's age (Black et al., 2009). Additionally, a distinct sorting pattern into locations with higher levels of social and human capital levels could be isolated. At the same time, job opportunities measured as skilled or unskilled vacancies did not matter for the general population, albeit males displayed location preferences for destinations with lower unemployment rates. A similar pattern could be established for Germany: destination choice of full-time employed men has been shown to be largely driven by economic conditions (Arntz, 2010).[43] Moreover, regional wage levels act as stronger attractors for high-skilled individuals. Immigrants display a higher level of sensitivity with respect to (expected) destination wage levels (Schündeln, 2014) and are more mobile across and within the 16 German states. The second finding can be seen as a direct consequence of a pronounced disparity between measures of unobserved costs of migration: the corresponding

[41] Furthermore, their approach allows deriving cross-marginal effects, which furnish information with respect to a location's relative attractiveness within the nexus of potential destinations.

[42] This specification requires a normalisation of derived marginal probabilities with respect to a reference community, i.e., one destination where the community dummy takes the value zero.

[43] In principal, the applied estimation procedure is a nested logit model. Locational choices, conditional on leaving the current location, have been estimated sequentially, thus the lower level in the decision tree is basically a conditional logit model. Findings from the upper level (the decision whether to move or stay) showed that individual attributes, such as age, income or earlier job moves are highly relevant for labour-market related mobility.

measure is 3.6 times as large for natives in the case of within state migration, and 3.2 times higher for inter-state migration scenarios.

Focusing on technical workers with a postgraduate degree, Dahl and Sorenson (2010) converted coefficients from a conditional logit model into monetary equivalents for compensating increasing distance to various social reference persons: doubling the distance to parents, this equivalent amounted to almost $ 5300 for those who changed their employer. Moreover, this amount surged to nearly $ 13000 a year for high-skilled workers whose previous employer closed down, hence whose staying option basically melted into thin air. In general, the valuation of spatial proximity to (social) anchor points was found to be more pronounced than the valuation of incomes.

4.2.2 Alternative estimation methods for discrete location choices

Oosterbeek et al. (1992) applied a multinomial logit approach to qualify factors that led to students' choice amongst the five universities in The Netherlands with an economics department.[44] In addition, they incorporated into their full structural model an estimate for expected earnings to control for expected returns to a specific enrolment decision. Most interestingly, the moderate positive effect of university-specific expected life-time earnings on selection probabilities vanishes when the multinomial logit model also comprises individual-specific attributes – utility seems to be predominantly shaped by preferences beyond earnings. This manifested for instance in a certain degree of sorting alongside paternal education-levels or a university city's attractiveness.

Separating attendance and location choice, Montgomery (2002) applied a nested logit model to examine enrolment choices into a graduate programme.[45] Individual ability, measured by GMAT scores, fostered in general enrolment in the attendance nest. A general preference for schools with a more able student body or a top ranking position could be observed in the school choice nest. Most interestingly, final school choice was heavily affected by geographic proximity although it was not relevant for stated 'first choice' schools: while an initial choice set may comprise a variety of (geographically) distinct alternatives, the final choice seems often to be restricted by distance.

Within a choice set composed of 26 destinations in the Stockholm area, Dahlberg and Eklöf (2003) compared the performance of a classical conditional logit specification, a mixed logit and a multinomial probit model.[46] One of their essential conclusions was that in their short-distance

[44] The distinction between a conditional and a multinomial logit model is that the latter has one alternative declared as reference alternative. Therefore, results can be interpreted in comparison to this reference alternative, leading to an interpretation of relative choice probabilities or sorting behaviour.

[45] In contrast to a conditional logit model, the nested logit model allows for higher levels of substitutability between some alternatives without necessarily implying a violation of the independence from irrelevant alternatives assumption (IIA) in general. Nests are supposed to reflect some plausible grouping, e.g., destinations in state A in one nest and destinations in state B in the second. This approach accounts for unobserved correlation among the destinations in one state, yet allows maintaining the IIA across nests.

[46] Mixed logit (or random parameter) models do not impose any restriction on substitution patterns. Moreover, they account for individual (random) taste variation by introducing individual specific parameters. Their distribution, however, has to be predefined. Similar to the multinomial logit model, the multinomial probit model requires the definition of one reference alternative. An advantage is that it can feature case-specific individual variables. Moreover, an estimation of the

migration setup, the conditional logit model could not be rejected in favour of the more flexible mixed logit specification. Instead, diverging results occurred only for 'overly' frugal specifications. Replacing the multinomial probit by a nested logit model, Christiadi and Cushing (2007) transferred the model evaluation to the case of US interstate migration, also detecting a fairly similar performance regarding coefficient signs and magnitude, as well as significance.[47] The same observation was made by Schündeln (2014), investigating German interstate migration patterns and contrasting conditional logit models with nested logit specifications, relying on three coarse nests (East, West and staying).

Average coefficients related to distances to reference persons or destination population size from a mixed logit model evinced a high degree of comparability to those from a conditional logit specification in the case of Danish high-skilled workers (Dahl and Sorenson, 2010). In the context of recreational demand, too, conditional logit models accounting for taste heterogeneity can compete with random parameter (mixed) logit specifications (Murdock, 2006): unemployed individuals, for instance, are less deterred by travel distance to their chosen recreational site.

Although unobserved similarities between alternative destinations in activity-based models impose conceptual issues, spatially correlated models (accounting for correlation across neighbouring alternatives) produce coefficient estimates which are of remarkable similarity to those from a conditional logit model (Bekhor and Prashker, 2008).[48]

As a modification to the mixed logit model, Greene and Hensher (2003) proposed a latent class model to account for individual heterogeneity, whilst relaxing a core requirement in the mixed logit model: instead of predefining parameters' exact distributions it is sufficient to specify a number of latent classes, into which individuals are implicitly sorted. In the context of stated road choices, the classical conditional logit specification was rejected in favour of both the mixed logit and the latent class specification. Choice elasticities for travel time and travel costs across all choices, however, were in a close range only in case of the latent class model specification and, most remarkably, the classical conditional logit.

Greene et al. (2006) incorporated behavioural variation into what they called a heteroscedastic mixed logit model by allowing not only the mean of the random parameters to be affected by individual-specific attributes but also the variance. In terms of model-fit for stated choices amongst commuting modes, the conditional logit is outperformed. Turning to relevant model outcomes, such as values of travel time savings, figures from the conditional logit and the standard mixed logit are

error's correlation structure relaxes the assumption of equal substitutability of alternatives, yet inflates the number of estimates.

[47] The authors also include age and education interactions, which turned out to be highly relevant predictors for locational choices.

[48] Activity-based models refer usually to non-work related destination choices for trips, e.g., shopping or for the purpose of recreational activities.

highly comparable.[49] Differences emerge when heteroscedastic parameter variances are introduced, yielding a better model fit, but these modifications "produce unacceptable ranges in the behavioural outputs, including negative VTTS estimates" (Greene et al., 2006, p. 91).[50] Though the methodological approach is rather sophisticated, and introduces actual behavioural variation and individual characteristics into a mixed logit model, results in the end are mostly different but not more plausible or reliable.

4.2.3 Choice set definition and stability of results

Making choices typically involves an initial stage, in which a consideration set is formed from an awareness set: here, a potential decision-maker compiles a set of relevant alternatives from all the alternatives he is aware of. In a subsequent (not necessarily isolable) stage, the consideration set may be further reduced to include only the most favoured alternatives.[51] Eventually, a decision-maker's resulting actual choice set is derived based on deterministic or probabilistic constraints,[52] which may be seen as "depending upon the degree of confidence the observer places on information at hand" (Swait and Ben-Akiva, 1987, p. 92). Thereby, awareness of alternatives and accessibility of related information seem to be influential factors in such a 'hierarchical information processing strategy' (Pellegrini and Fotheringham, 2002). In the context of spatial analyses, another factor is differences in "physical accessibility levels due to path limitations and due to differences in individuals' mobility levels" (Pramono and Oppewal, 2012, p. 48).

The aspect of destination awareness is also relevant in the context of college choice: high achieving students in the two top deciles are aware of a larger number of potential college locations (Niu and Tienda, 2008). This points to heterogeneous formation processes of choice sets, respectively their scope, conditional on ability. Across alternative choice sets, this variability on the individual level was also diffused to a varying degree to the estimates of institutional attributes of the most preferred alternative. In respect thereof, constraints may also exert differing effects on heterogeneous decision-makers.

Testing different modelling approaches for the formation of a consideration set, Horowitz and Louviere (1995) portended that these sets might be primarily indicators of preferences. Though additional information from an alleged consideration stage may not foster consistency, a gain in estimates' efficiency can be achieved nevertheless.

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[49] E.g., saving one hour of travel time is valued at $17.98 (derived in a conditional logit model) by those usually using public transport. The corresponding value from the mixed logit model (assuming a positive random parameter domain) is $16.62 with a standard deviation of $2.45.

[50] VTTS stands for values of travel time savings.

[51] The choice set formation process, including the consideration set, and its relevance is a frequently discussed topic in the consumer choice literature (cf. Shocker et al., 1991; Andrews and Srinivasan, 1995) or in vacation destination choice (cf. Crompton, 1992; Decrop, 2010), bearing some resemblance to destination choice in a migration context.

[52] A deterministic constraint in this work's application would imply categorical non-inclusion of an alternative (yet is hard to imagine). Probabilistic constraints could be imposed by fees - some individuals could not afford certain alternatives, or by familiarity with a location. Both aspects point immediately to highly subjective choice set formation processes.

If the concept of consideration sets is primarily introduced to reduce the dimensionality of the underlying choice problem, and thus for analytical convenience, simulations demonstrate that results may be severely affected: to small consideration sets may bias estimates towards zero, simultaneously increase their variance and reduce overall model fit (Carson and Louviere, 2014). This can also be found in empirical applications, i.e., a conditional logit model of office relocation choice when firm-specific search areas, analogous to consideration sets, are introduced (Elgar et al., 2015).

Comparing models relying on complete, vicinity-based and familiarity-based choice sets, Hicks and Strand (2000) examined the impact of information about choice sets on parameter estimates in scenarios of discrete recreational choices.[53] Whereas familiarity with an alternative becomes in general less likely with distance, estimates originating from predefined distance-based choice sets converge to the full choice set results' if the conditional distance is scaled up. This sensitivity is particularly marked for estimates corresponding to travel-related variables, which in turn can be seen as strong evidence against applying a too restrictive geographic conditioning. On the other hand, defining spatial boundaries of choice sets such that they include at least 95 % of all observed choice events was found to produce stable results (Parsons and Hauber, 1998).

Recapitulating these findings, one may conclude that the identification of the appropriate relevant choice set is at least as important as the selection of a suitable estimation procedure.

4.3 Data and descriptive statistics

The first subchapter introduces the data source providing information on potentially mobile academics. Moreover, it also discusses how information on considered locational alternatives at various stages of the decision-making process is elicited. In order to introduce the alternatives that decision-makers could choose from, the second subchapter illustrates some location specific characteristics of the potential alternatives in the destination space.

4.3.1 Microdata on decision-makers and choice sets

This study draws on a survey on "Mobility, Expectation, Self-Assessment and Risk Attitude of Students" (MESARAS 2013; Weisser, 2016a[54]), a cross-sectional survey which has been designed to provide both, detailed information on individual characteristics and preferences on the one hand, and multiple geo-referenced anchor points on the other. These geographic anchor points allow important mobility events to be traced. They also serve as pivotal points in subsequent analyses since they enable to calculate a precise measure of mobility, i.e., covered distance in kilometres.

The survey's target group composed of 2308 undergraduate university students, who started an economics programme at one of seven vicinal universities in northern and middle Germany in

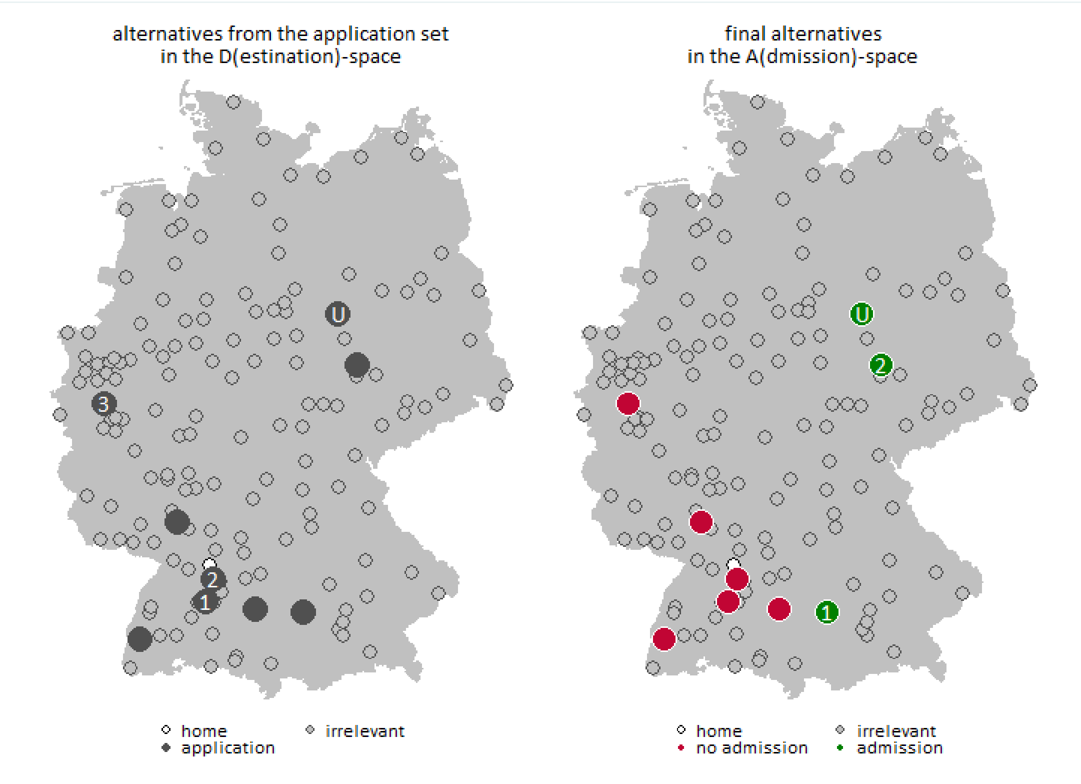
[53] Most interestingly, the full choice set is defined by all recreational sites of similar type in a region. This, however, implicitly imposes a geographic (de facto distance-based) constraint on the likelihood that any alternative is an element in this full choice set.

[54] The survey's representativeness could be established using administrative data. Further information regarding the sample and the methodology is provided in Weisser (2016b).

October 2013. The definition of such a homogeneous target group is suitable to minimise the impact of unobserved factors in the examination of mobility patterns: since economic programmes are offered at virtually any university in Germany, this restriction ensures that chosen destinations are actually outcomes from a choice process and not mostly predetermined by the interest in an exotic programme only available at few institutions. In total, there are 164 potential study locations (districts or district-free cities) with at least one institution of higher education offering an economics programme. In a narrow definition, based on curriculums' similarities, the following study programmes are rated as economics programmes: Business Studies, Economic Studies, International Management and Economics and Business. A broader definition also includes Business Informatics, Engineering Economics and Economic Policy Journalisms.[55]

Figure 4.1 displays the geographic distribution of the 164 alternative destinations, defining the full destination space D. The left panel refers to the application stage of a figurative individual, the right panel shows the corresponding outcome in the admission space A, hence after the supply side decision has imposed some further restrictions on the set of potential destinations. The hollow circles represent all potential alternatives that have never been considered, whereas the filled circles indicate a study location this figurative individual has applied for. Aside from the eventually chosen alternative (labelled 'U'), the three most preferred alternatives at each stage are observed as well.

Figure 4.1: Decision-makers' alternatives in the full and restricted space



Note: The left panel depicts the full application set (sent applications in the D-space for a fictitious individual), the right panel illustrates the final alternatives in the admission set (the A-space).

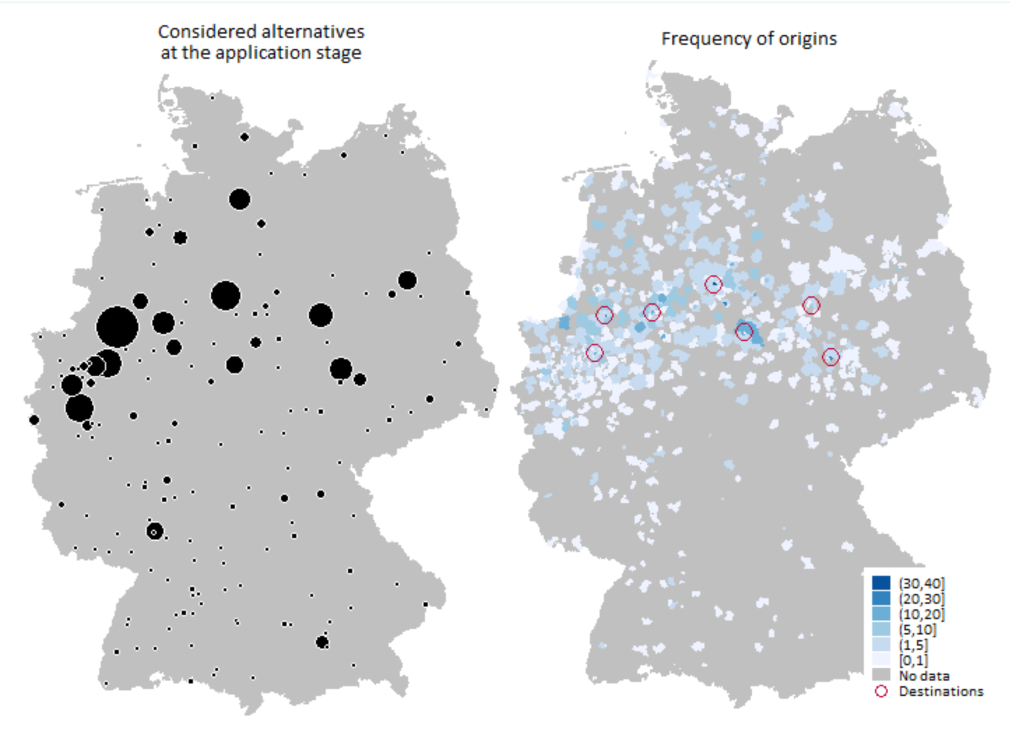
[55] Institutions offering economics programmes in a broader sense usually offer Business Studies or Economics and Business as well. Within the empirical analysis, robustness checks account for differing degrees of programme availability (Table A4.9).

Another design related restriction led to the exclusion of study programme changers to ensure that all study subjects made a choice with respect to a study location for the first time. Students from abroad, i.e., those who graduated from high school in another country, were also taken out of the sample since previous geographic anchor points are too imprecise. Eventually, this study's target sample comprised a total of 1861 individuals.

Among these individuals in the study target sample, 69 % actually had an alternative admission for an economics programme. Around 55 % in this group eventually chose the closest available alternative. Going one step back and focusing on the locations initially applied for (indicating demand), 23.2 % sent out only a single application. 11.6 % selected two potential locations, 19.4 % applied at institutions in three distinct locations. The majority (45.9 %) included into their application set at least four alternative destinations.

The left panel in Figure 4.2 illustrates how frequently one of the 164 potential destinations has been either finally selected or mentioned as being one of the three most preferred alternatives at the application stage. The right panel contrasts this with individuals' origin.

Figure 4.2: Geographic distribution of origins and considered destinations



Note: Circles in the left panel are approximately proportional to their relevance in the set of most preferred or finally selected alternatives in the application stage. 'Frequency of origins' in the right panel refers to the number of students who originated from a specific postal code area and enrolled at any among the seven included universities, labelled as destination.

Two main observations can be made: individuals displayed in the end a tendency to enrol at an institution in relative proximity to their origin. On average, respondents in the study target sample chose a study location within 97.15 kilometres of their origin, the latter identified as the city they graduated from high school. There are, however, remarkable differences of observed mobility with respect to varying personal characteristics, as Table 4.1 reveals. Least patient or most risk-averse individuals seem to enrol at closer institutions in comparison to those on the other end of the scale. Moreover, those expressing a strong preference for proximity to family behave accordingly when it comes to the choice of a study location.

Table 4.1: Observed mobility (in km) and personality characteristics

	low	medium	high
risk attitude (career domain)	87.9	96.3	106.5
patience	92.5	94.6	115.7
importance of proximity to family	127.4	92.4	77.2

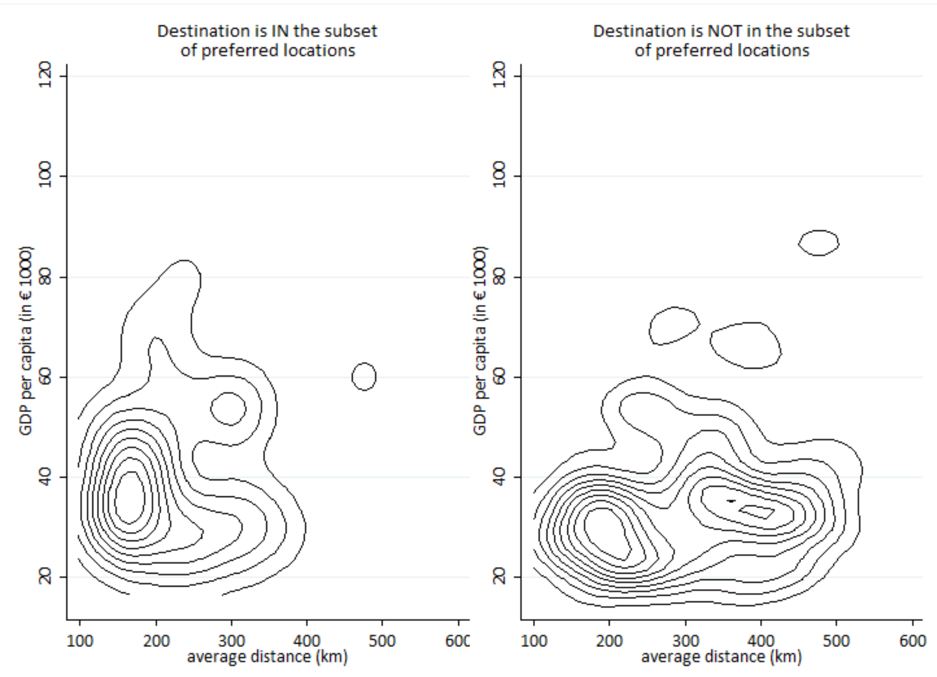
Note: Columns refer to standardised indicators where ‘low’ indicates a score of more than one standard deviation below the mean, and ‘high’ a score of more than one standard deviation above the mean. Sample size varies between 1811 and 1844 respondents across the traits.

The second conclusion to be drawn based on Figure 4.2 is that prospective academics in the study target sample do initially consider many potential destinations further away. City states, like Berlin or Hamburg, are frequently mentioned as most preferred study alternatives where someone actually applied for an economics programme. Study locations, especially those in metropolitan areas appeal to the young academics in the sample. Nevertheless, there is a substantial degree of variation in a geographic sense regarding considered alternatives in the destination space.

4.3.2 Characteristics of alternatives in the destination space

Acknowledging the observed preference patterns, Figure 4.3 to Figure 4.6 display for all 164 potential destinations bivariate kernel density estimates of one location-specific condition (depicted on the vertical axis) and individuals’ mobility (on the horizontal axis), measured as average distance to individuals’ origins. All location-specific data originates from the INKAR online database (BBSR, 2014) and refers to the district level. The reference year is 2012, which is the last complete year before respondents in the sample made their decision.

Figure 4.3: Bivariate kernel density – destinations’ GDP per capita and distance

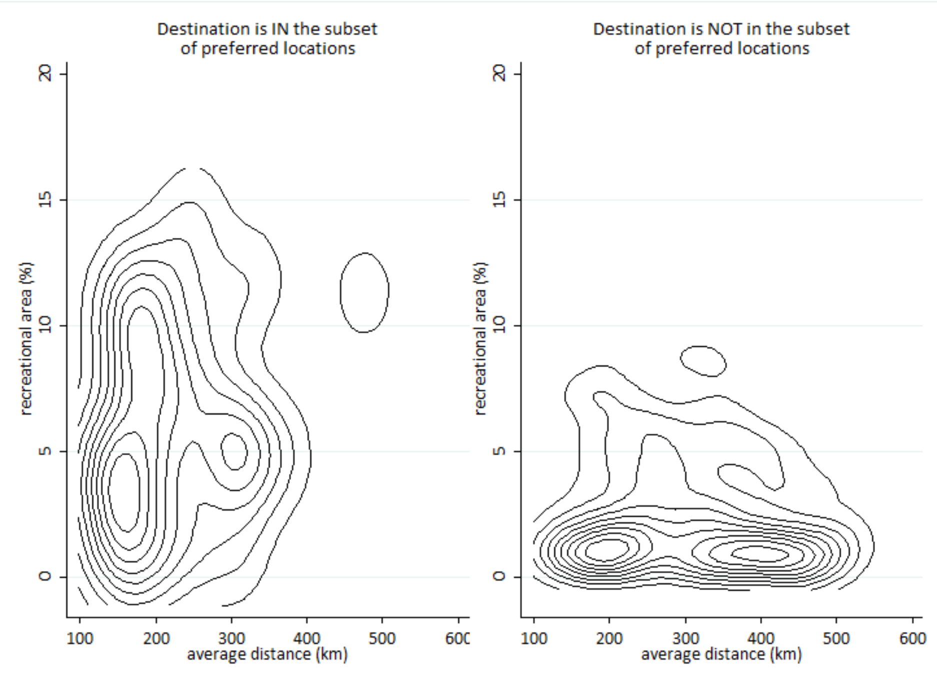


The left panels refer to locations that have been either eventually chosen or belonged (for at least one per cent of the subjects) to the three most preferred considered locations at the application stage. Concurrently, the right panels illustrate the cases of locations either not considered as the most preferred alternatives (of at least one per cent of the included individuals) or which have in deed not been considered at all. The graphs can be read like a topographical map: going from outer to inner lines, the portrayed contour lines indicate an increasing joint density.

As Figure 4.3 highlights, not considered or not preferred locations (right panel) are typically characterised by lower GDP per capita, a proxy for income levels or living standards, and are on average further away from an individual's origin. Destinations in the subset of preferred locations (left panel) are concentrated in the vicinity of € 35000 GDP per capita and an average distance of 170 kilometres.

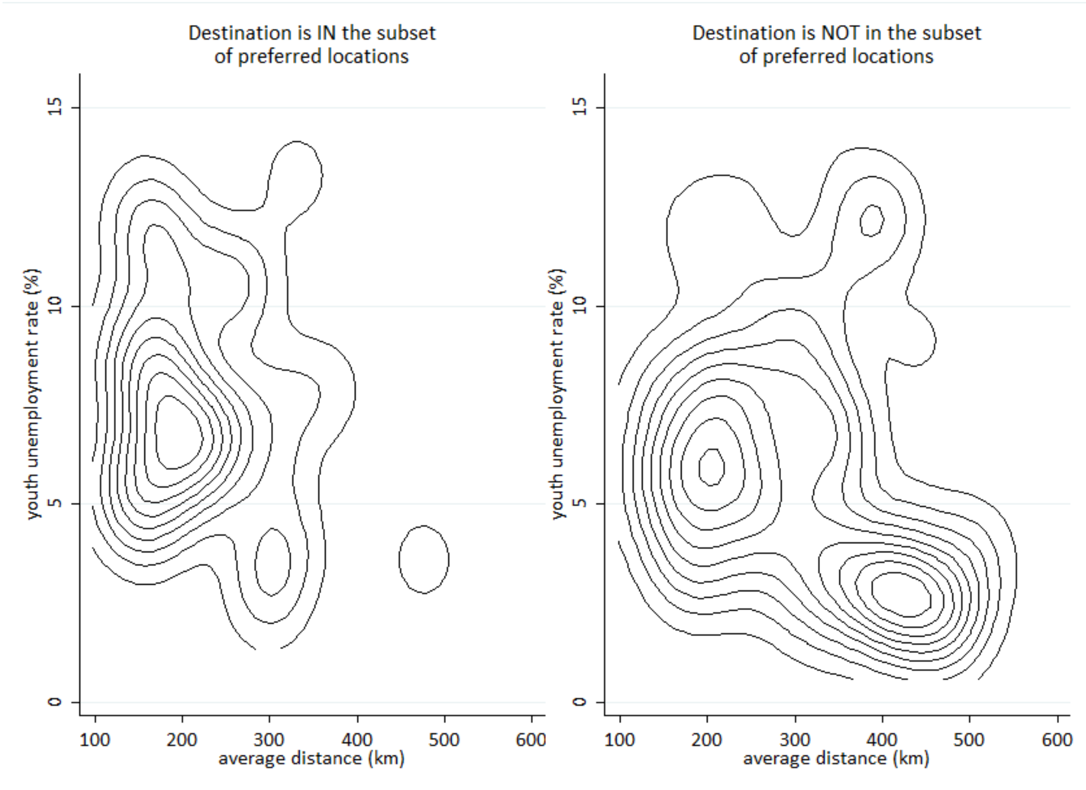
For the destination specific share of recreational area (Figure 4.4), which can be interpreted as proxy for quality of life, an even clearer picture emerges: considered locations exhibit distinctly higher recreational potential. Additionally, they are on average much closer to a respondent's previous centre of life.

Figure 4.4: Bivariate kernel density – destinations' recreational area and distance



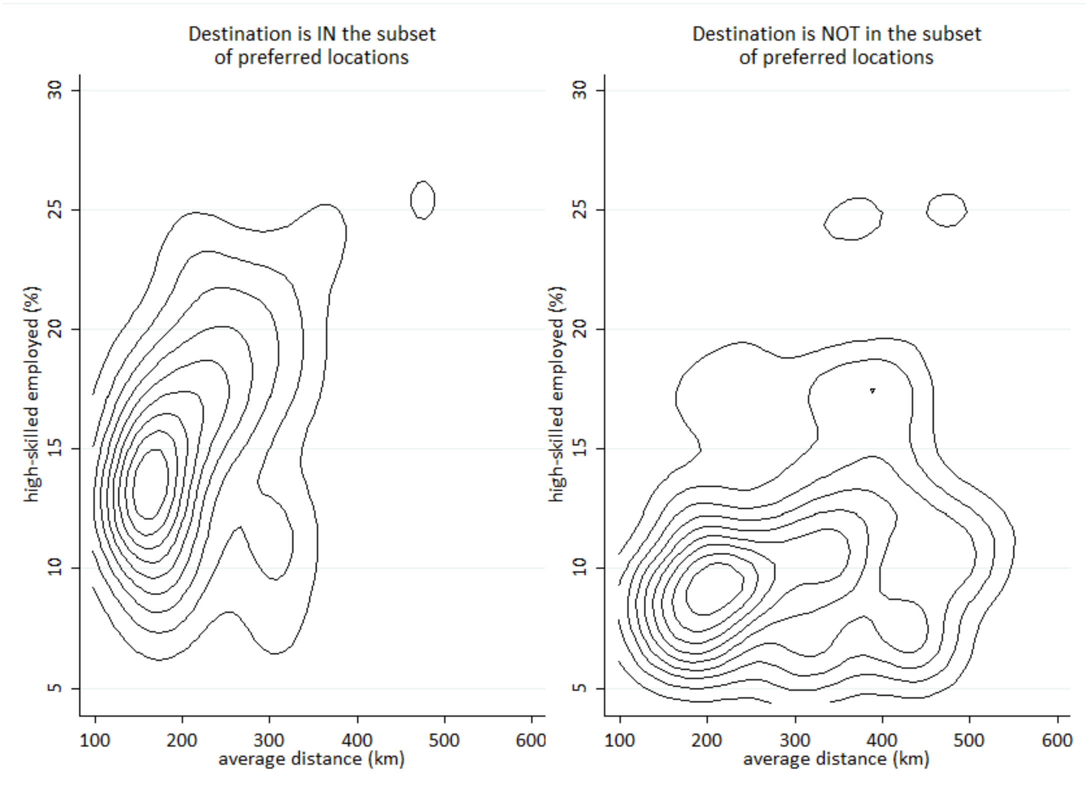
Regarding labour market perspectives, some first insights can be obtained on the aggregate level as well. For both types of destinations, those in and those not included in the subset of preferred locations, a cluster surfaces in the vicinity of 7 % youth unemployment rate and 200 kilometres distance. A second distinct cluster also emerges for a much lower unemployment rate and 420 kilometres distance between origin and destination (right panel in Figure 4.5). Though a lower youth unemployment rate could signal better employment perspectives for students during their studies, these potential locations are usually not considered.

Figure 4.5: Bivariate kernel density – destinations' youth unemployment rate and distance



In contrast to the previous finding, there is also descriptive evidence that the analysed young academics did not completely lose track of future labour market perspectives. Their initial application set tended to include those destinations with higher employment levels for high-skilled workers, as measured by the proportion of workers with university degree (Figure 4.6).

Figure 4.6: Bivariate kernel density – destinations' high-skilled employment and distance



The descriptive analyses in Chapter 4.3.1 and Chapter 4.3.2 accentuated some choice patterns, which are not only related to destination-specific features, but also affected by individual characteristics. People tend to sort into locations not only based on expected returns, as indicated for instance by labour market related preferences, but also based on individually varying assessments and preferences. The interaction of these individual characteristics and destination features, yielding a form of behavioural sorting will thus be further addressed in a framework acknowledging the existence of heterogeneous agents.

4.4 Heterogeneous agents and varying information sets in a random utility framework

The workhorse of this study is a random utility model (RUM) and its econometric counterpart, the conditional logit model. Despite its limitations, i.e., the assumption of independence from irrelevant alternatives (IIA), it offers some advantages for this application.[56] First of all, it does not require specifying nests of alternatives, which might be irrelevant from an individual's perspective, as a nested logit model warrants. Second, in contrast to mixed logit models, the focus does not rest on abstract distributions, but rather on actual personality or preference patterns in the decision-making process. Therefore, heterogeneous dependencies are introduced by directly implementing plausible interactions following structured personality groupings or according to distinct preferences. This allows drawing inference with respect to the relevance of a specific destination condition, and thus its impact on a potential destination's selection probability for various sub-groups (cf. Liaw, 1990; Elgar et al., 2015).[57] Last but not least, the chosen approach relaxes severe computational limitations in a high-dimensional destination and parameter space while, as the literature review suggests (cf. Greene and Hensher, 2003; Murdock, 2006; Bekhor and Prashker, 2008; Dahl and Sorenson, 2010), it is able to produce estimates in a comparable range as more sophisticated models.

4.4.1 A conditional logit model for heterogeneous agents

Assuming that every individual i evaluates a potential location l (with $l \in D$) based on the corresponding utility U_{il}, the individual's decision can be represented by a random utility model (McFadden, 1973). A location l is chosen if

$$U_{il} > U_{ij} \text{ for all other } j \neq l \text{ and } j \in D$$

or

$$U_{il} \geq U_i^*.$$

[56] This is further addressed in Chapter 4.5.3. The IIA can be relaxed using nested logit or mixed logit models. In the first case, the IIA can still be an issue within nests of alternatives. Mixed logit models account for individual taste variation but not for a specific taste or personality grouping. In this application, characterised by a larger than usual choice set and a rich vector of personality and preference parameters, computational challenges are substantial.

[57] Liaw (1990) used these interactions between 'ecological' variables and individual characteristics in a model of interprovincial migration by young Canadians. The destination choice model at the second stage of the underlying nested logit model, however, is basically a conditional logit model. Elgar et al. (2015) investigated location choices of different types of firms in the Toronto area.

The first case represents the final destination choice among all considered alternatives in an unrestricted destination space D. Mirroring the application stage, the second case accommodates choices yielding a set containing several alternatives, which are preferred over the remaining alternatives.

If utility is linear in parameters relating to a vector z_{il} and disturbances ε_{il}, the probability that an alternative l is selected is given by

$$P(l|z_{il}) = P[z_{il}\omega + \varepsilon_{il} > z_{ij}\omega + \varepsilon_{ij}, \forall\, j \in D|j \neq l]\ . \tag{4.1}$$

If the random error term ε follows a type 1 extreme value (or Gumbel) distribution, the conditional logit model states the probability that alternative l is selected among all D=164 possible alternatives in the destination space as

$$P(l|z_{il}) = \frac{\exp(z_{il}'\omega)}{\sum_{l=1}^{D}\exp(z_{il}'\omega)}. \tag{4.2}$$

This econometric procedure allows detecting which location-specific factors affect a destination's selection likelihood. It is, however, in its standard specification not suitable to identify the impact of subject-specific characteristics on the corresponding selection probability. If the vector z_{il} comprises location-specific variables x_{il} and some individual characteristics, summed in the vector v_i, the latter cancels out in equation 4.2. The subsequent specification, accounting for individual specific factors, serves as the starting point to illustrate this issue and a possible remedy together:

$$P(l|z_{il}) = \frac{\exp(v_i'\alpha + x_{il}'\beta + [V_i X_{il}]'\gamma)}{\sum_{l=1}^{D}\exp(v_i'\alpha + x_{il}'\beta + [V_i X_{il}]'\gamma)} \tag{4.3}$$

Location and individual-specific factors are combined by the matrix vector product $[V_i X_{il}]'$, which introduces interaction terms.[58] This equation can be rearranged into

$$P(l|z_{il}) = \frac{\exp(v_i'\alpha)\exp(x_{il}'\beta + [V_i X_{il}]'\gamma)}{\exp(v_i'\alpha)\sum_{l=1}^{D}\exp(x_{il}'\beta + [V_i X_{il}]'\gamma)} = \frac{\exp(x_{il}'\beta + [V_i X_{il}]'\gamma)}{\sum_{l=1}^{D}\exp(x_{il}'\beta + [V_i X_{il}]'\gamma)}\ , \tag{4.3'}$$

demonstrating why all non-interacted individual level components are not identified in a conditional logit model. The joint impact of individual characteristics and location-specific variables may be retrieved in the coefficient vector γ. Therefore, it is possible to evaluate whether different types of individuals, for instance differing by risk attitude, have diverging elasticities with respect to certain destination-specific conditions, such as unemployment rates. Conveniently, coefficients of interactions of individual characteristics and distance can be interpreted as measures for heterogeneous costs of migration.

Another merit of introducing individual characteristics into the model is that it also accounts for an individual specific choice set formation process, which has further repercussions on the final choice. Directly controlling for individual factors contributes then to a better understanding of the unexplained variation across individuals concerning their location choices. In case of a high-

[58] Vectors $x_{il}$and X_{lk} are both of dimension $m \times 1$ with m as number of location-specific factors. X_{il} is allowed to differ from x_{il} in so far as it may contain a smaller number of non-zero elements than m, corresponding to the number of factors to be interacted. The matrix V_i is of order $r \times m$ with r as total number of individual specific categories to be interacted. Within each row r, columns m contain identical entries, such that V_i matches the dimension of X_{il}.

dimensional destination space, this direct approach averts the necessity to resort to circuitous models of choices from endogenous choice sets (cf. Horowitz, 1991).

A crucial assumption in conditional logit models is the independence from irrelevant alternatives (IIA), which becomes more plausible for choice sets containing alternatives of similar substitutability (McFadden, 1973). In such cases, a newly added alternative would be associated with a selection probability of p_{D+1} whereas selection probabilities of all D old alternatives would be proportionally diminished to $(1-p_{D+1})p_D$. While alternative study locations might be perceived to be of comparable substitutability in a scenario which evolves mainly around the decision to study or not to study, this scenario is different. In this application, focusing on location choices of those who selected themselves into a specific study programme, the final choice of a destination is based on a choice set comprising rather distinct alternatives: university cities (and districts) in Germany display a high degree of variation regarding location-specific characteristics (x_{il}), e.g., with respect to city size, economic conditions or price levels. These differences might introduce varying degrees of substitutability among some subsets of alternatives, and thus potentially violate the IIA. This issue is further explored in Chapter 4.5.3.

4.4.2 The impact of varying information sets in a conditional logit model: A Monte-Carlo simulation study

One of the central research questions guiding this work is how differing information sets can impinge on estimates in models of discrete destination choice. A first pivotal aspect of the information set is related to *what the analyst observes* in the data. Typically, only the final choice without comprehensive information on considered alternatives or supply side restrictions is observed.

Supply side restrictions might emerge whenever an observable location choice is the outcome of an interaction of one individual and one institution, e.g., an employer or a university. Any finally observable location choice was not only conditional on individual application (a first decision stage), but also on subsequent institutional acceptance or admission. If the second stage always results in a successful match, e.g., due to guaranteed acceptance, the ultimately observable choice should correspond to the considered alternative yielding the highest utility in a random utility framework.

Whenever subsequent acceptance is required, however, this may change: most preferred considered alternatives (yielding highest levels of utility) might drop out of the eventually available choice set. Whilst a rational individual would still choose the respective alternative associated with the highest utility in this second-stage choice set, the final recorded choice could be a rather inferior alternative in the initially considered choice set.[59] Usually, these interactions and potential restrictions cannot be observed by the analyst, although they may affect estimates' reliability in a random utility framework severely.

[59] In the most extreme scenario, the final observed choice (characterised by relatively low utility levels in the first stage choice set) could be no choice at all, but rather the inevitable outcome due to the lack of feasible alternatives. This would reflect individuals' preferences only to an extremely low degree.

For modelling discrete choice, however, another crucial aspect of the information set is *what the analyst assumes*: this refers to the more general question about how to appropriately define the underlying choice set, i.e., the destination space. In case of choice set misspecification, the econometrically deduced impact of factors influencing location choices might be severely biased. This has been observed in the fields of recreational choices (Hicks and Strand, 2000; Parsons and Hauber, 1998) and intra-urban office relocation (Elgar et al., 2015). The same will hold in all likelihood for a consequential decision, such as where to study and live for the next few years.

In order to evaluate whether more comprehensive information sets, accounting for explicitly considered alternatives, can contribute to uncovering the underlying mechanisms and individual preferences, a Monte-Carlo simulation study is performed. The design of this simulation study accounts for various information sets, misspecification in parameters and in the error term. In addition, it precisely portrays the three decision stages within the selection of a study location, namely application process, admission process and destination selection in the end. Therefore, I can also examine how strongly a supply side restriction might affect estimates of location choice. At the same time, I can investigate how relevant the first critical aspect regarding the analysts' information set, i.e., an insufficient observability of the choice process itself, can become. The second aspect, namely, estimates' sensitivity with respect to the definition of the destination space will be addressed in the empirical application directly.

A specific feature of the simulation design is to maintain real-world location-specific conditions, i.e., to randomly place simulated individuals into real cities and districts. Therefore, the simulation algorithm starts by drawing 1000 'blank' individuals (with replacement) from a list of 401 existing districts of origin. The district sampling probability is proportional to the district's population, thus the simulated samples comprise on average twice as many simulated individual from Berlin (3.5 million inhabitants) than from Hamburg (1.8 million inhabitants). Individual-specific variables v_i, such as gender, age, risk attitude and grade were generated in the next step and are based on random draws from distributions mirroring observed sample properties.[60]

Subsequently, the initial sample of 1000 simulated individuals has been expanded to include the full set of $D = 164$ potential locations for each individual. Destination-specific conditions, such as district unemployment rates or population density have been appended next and constitute matrix x_{il}.[61]

The subsequently implemented data generating process (DGP) simulates individual and alternative specific utility levels as

$$U_{il} = z_{il}'\omega + \varepsilon_{il} = x_{il}'\beta + [V_i X_{il}]'\gamma + \varepsilon_{il}. \tag{4.4}$$

[60] Distributional properties and correlations are described in Table A4.1 (in the appendix). The in-sample values, serving as reference values can be found in Table A4.2 (in the appendix).

[61] The essential item ‚distance' has been calculated as average distance between all postal code areas (centroids) in the district of origin and the centroid of a respective postal code area with a higher education institution in the destination district.

The correct specification of the error component is implemented with $\varepsilon_{il} = e_{il}^{G} \sim i.i.d.\ Gumbel(0,1)$. With respect to the conditional logit model, a first misspecification in the error is introduced with $\varepsilon_{il} = e_{il}^{N} \sim i.i.d.\ N(0,1)$. In a third specification, correlated error components at the individual level are derived as $\varepsilon_{il} = e_{il}^{G}(0.5 + e_{i}^{U})$ with $e_{i}^{U} \sim i.i.d. U(0,1)$.[62]

The implemented main DGP draws on the following parameterised form:

$$U_{il} = \begin{pmatrix} avg.distance \\ pop.density \\ recr.area \\ unemp.rate \end{pmatrix}' \begin{pmatrix} -0.0080 \\ 0.0015 \\ 0.0150 \\ -0.3000 \end{pmatrix} + \begin{pmatrix} avg.distance\#age \\ avg.distance\#risk-averse \\ avg.distance\#risk-loving \\ pop.density\#age \\ recr.area\#age \\ unemp.rate\#age \\ unemp.rate\#uecgrade \\ unemp.rate\#risk-loving \end{pmatrix}' \begin{pmatrix} -0.0002 \\ -0.0015 \\ 0.0010 \\ -0.0001 \\ -0.0005 \\ 0.0150 \\ 0.0150 \\ 0.0500 \end{pmatrix} + \varepsilon_{il}$$

The components in the coefficient vectors β and γ have been determined based on an initial conditional logit estimation on the real data. To denote interactions between variables on the location and the individual level, the symbol # is used.

Building on these utility levels, individual selection probabilities for $D = 164$ alternative destinations were calculated accordingly to equation (4.3'). The simulation of the first stage (the application process) is completed by simulating the size S of the individual application set C_0. Since the overall number of sent applications may not be purely random, but for instance related to individual willingness to take risks, this simulated initial application set of size $S_{C_0} \in [1, D]$ is negatively correlated with the risk variable.[63]

The admission process is then incorporated based on simulated admission likelihoods. Since the simulated sample is supposed to mirror the real sample (all consisting of enrolled, thus successful students), one sure admission is modelled for the location with the highest admission likelihood. Scholastic achievement is, furthermore, inversely related to additional admissions, such that individuals with the top grade obtain admission at all considered locations. This success probability declines with lower scholastic achievement, yielding an admission set C_1 of size $S_{C_1} \leq S_{C_0}$.

In the third and last step, simulated enrolment choices are based on the outcomes from the main DGP, such that the following two conditions hold for the eventually chosen location l^*:

$l^* \in C_1$ and

$U(l^*) > U(l_{C_1})\ \forall\, l_{C_1} \in C_1,\ l_{C_1} \neq l^*.$

This merely requires the eventually chosen location l^* to be in the final admission set C_1 and yielding the highest utility in comparison to all other alternatives in this final set.

Drawing on the choice sets C_0 and C_1, three outcome variables can be established, differing with respect to the information set under consideration. A first one indicates the final choice within the

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[62] A multiplicative construction of a clustered error component is required for the same reasons as for why individual-specific variables have to be included as interaction terms.

[63] The initial (complete) choice set C_0 comprises those alternatives yielding the S_{C_0} highest levels of utility. S_{C_0} is based on draws from a negative binomial distributions (see Table A4.1)

subset of itself and the 'stated most preferred' alternatives with admission, which is of size $S_{C_1^{obs}} \in [2,4]$.[64] The upper bound corresponds to the bound implied by the survey design. The resulting outcome variable, labelled 'choice in A', is coded as one for l^* and zero for all other $l_{C_1} \in C_1^{obs}$.

The second outcome variable 'choice in D' represents the final choice within the full set of all D potential alternatives. It is coded as one for l^* and zero for all other $D-1$ alternatives. This version does not necessarily allow retrieving much information regarding true location preferences, since the observed outcome might be driven to a lesser extent by individual preferences but by the admission process. The third outcome variable 'preferences in D' takes into account the final choice and the 'stated most preferred' alternatives in the initial selection process. It is $S_{C_0^{obs}}$-times coded as one (for l^* and for those alternatives yielding the $S_{C_0^{obs}} \in [1,4]-1$ highest levels of utility) and zero for the remaining $D - S_{C_0^{obs}}$ alternatives. Technically, this specification violates mutual exclusiveness of choices for any $S_{C_0^{obs}} > 1$. Yet, in the context of observed choices, which depend on a subsequently exogenously restricted choice set, an increased information set can still be an indicator of preferences (Horowitz and Louviere, 1995) and help to mitigate the distorting impact of such a second-stage influence on estimated coefficients.

Table 4.2 summarises the estimation results for the three different outcome variables and three model specifications. The first value in each cell is the mean coefficient estimate over the 500 simulated samples; the second number represents the number how often a coefficient has been significant on the 5 % level. The specifications vary with respect to their parameterisation, i.e., to which extent location-specific conditions are interacted with individual-specific factors (none, partial and full).

As simulation results in Table 4.2 indicate, estimations based on the exogenously restricted choice set (choice in A) are neither suitable to get precise estimates nor to identify whether a factor may be actually relevant in the decision process. This occurs mainly for two reasons: first, only a subsample of individuals has a final choice set of size $S_{C_1^{obs}} \in [2,4]$. Since the simulated supply side restriction is ability related, as in universities' admission processes, this sample reduction is not completely random. Second, a lot of information is discarded since the choice set is only assumed to comprise between two and four alternatives per individual. Estimations which evaluate a final choice in the full space of all D alternatives (choice in D) perform better in this regard: not only do estimated coefficients come close to the true parameters in the main data generating process, but the respective standard errors are smaller as well. As expected, the most parsimonious specification without any interactions produces nevertheless substantially biased estimates. The fully interacted specification is more reliable in this regard: the estimates expected value hardly indicates any bias at all. Beyond that, estimates not driving the DGP are exposed as well: the count of allegedly significant

[64] It only includes those simulated individuals who actually had a choice between at least two alternatives with admission.

coefficient estimates at the 5 % significance level is close to 25. For 500 simulated samples, this corresponds exactly to the test's nominal significance level.

Table 4.2: Simulation results for varying information sets (type 1 extreme value specification)

$u_{il} \sim i.i.d.$ $Gumbel(0,1)$		information set (estimated specification)								
		preferences in D (I)			choice in D (II)			choice in A (III)		
observed location choices		$S = 4$			$S = 1$			$S = 1$		
destination space		$D = 164$			$D = 164$			$A \in [2,4]$		
model	DGP	none	partial	full	none	partial	full	none	partial	full
$\boldsymbol{x_{il}}$: average distance	-0.0080	-0.01243	-0.00799	-0.00791	-0.01197	-0.00814	-0.00817	-0.00053	0.00022	0.00023
		(500)	(464)	(457)	(500)	(309)	(307)	(66)	(24)	(24)
gender # x_{il}	0		-0.00033	0.00000		-0.00029	0.00000		0.00003	0.00006
			(54)	(25)		(27)	(19)		(26)	(25)
age # x_{il}	-0.0002		-0.00022	-0.00022		-0.0002	-0.0002		-0.00004	-0.00004
			(245)	(245)		(99)	(103)		(22)	(22)
uecgrade # x_{il}	0		0.00001	0.00001		0.00013	0.00013		-0.00003	-0.00003
			(23)	(24)		(27)	(25)		(28)	(27)
risk-averse # x_{il}	-0.0015			-0.0016			-0.00143			-0.00026
				(391)			(149)			(26)
risk-loving # x_{il}	0.0010			0.00102			0.00087			-0.00002
				(141)			(74)			(25)
$\boldsymbol{x_l}$: population density	0.0015	-0.0005	-0.00157	0.00157	-0.00049	0.0015	0.00149	-0.00003	0.0002	0.00019
		(500)	(490)	(491)	(500)	(319)	(312)	(31)	(27)	(26)
gender # x_l	0		0.00000	0.00000		0.00000	0.00000		-0.00002	-0.00002
			(22)	(22)		(18)	(20)		(24)	(24)
age # x_l	-0.0001		-0.0001	-0.0001		-0.0001	-0.0001		-0.00001	-0.00001
			(500)	(500)		(456)	(454)		(23)	(24)
uecgrade # x_l	0		0.00000	0.00000		0.00000	0.00000		-0.00001	-0.00001
			(23)	(23)		(19)	(20)		(32)	(24)
risk-averse # x_l	0			0.00000			0.00000			0.00000
				(27)			(27)			(26)
risk-loving # x_l	0			-0.00001			-0.00001			0.00002
				(29)			(25)			(16)
$\boldsymbol{x_l}$: recreational area (p.c.)	0.0150	0.00525	0.01586	0.01585	0.00485	0.0152	0.01517	0.00047	0.0012	0.00117
		(500)	(479)	(481)	(500)	(309)	(309)	(38)	(34)	(31)
gender # x_l	0		0.00001	0.00001		0.00000	0.00001		0.00002	-0.00003
			(33)	(33)		(27)	(24)		(26)	(30)
age # x_l	-0.0005		-0.00053	-0.00053		-0.00051	-0.00051		-0.00005	-0.00005
			(390)	(392)		(197)	(196)		(24)	(21)
uecgrade # x_l	0		0.00001	0.00001		-0.0001	-0.0001		0.0001	0.00011
			(26)	(27)		(20)	(21)		(26)	(34)
risk-averse # x_l	0			-0.00001			-0.00014			0.00032
				(25)			(21)			(27)
risk-loving # x_l	0			-0.00017			-0.00012			-0.0005
				(27)			(24)			(20)
$\boldsymbol{x_l}$: unemploy-ment rate	-0.3000	0.04081	-0.30723	-0.31507	0.04298	-0.28255	-0.29240	0.00155	-0.02776	-0.02989
		(492)	(428)	(433)	(401)	(215)	(224)	(26)	(27)	(25)
gender # x_l	0		-0.00374	0.00124		-0.0056	0.00037		0.00048	0.00142
			(29)	(25)		(23)	(27)		(24)	(29)
age # x_l	0.0150		0.01578	0.01576		0.01479	0.1477		0.00107	0.0012
			(463)	(465)		(270)	(265)		(28)	(27)
uecgrade # x_l	0.0150		0.01477	0.01475		0.01386	0.01375		0.0036	0.00329
			(83)	(80)		(35)	(33)		(31)	(30)
risk-averse # x_l	0			-0.00089			-0.00073			-0.00237
				(23)			(24)			(36)
risk-loving # x_l	0.0500			0.05338			0.05215			0.00386
				(193)			(114)			(21)

Note: The DGP-column presents the true parameters used in the data generating process (DGP). All results originate from a simulation, based on 500 replications and a simulated sample size of 1000. The first value in each cell is the average estimated coefficient, the value below stands for the number of estimated coefficients, which are significant at the 5 % level. Specifications 'none' are based solely on the vector x_{il} of location specific variables. Specifications labelled 'partial' draw on an interacted model ($v_i x_{il}$) without the two risk indicators. Specifications 'full' include all (interacted) variables involved in the DGP. In case of the most restricted choice set, with $A \in [2,4]$, all simulated individuals with only one alternative have been dropped (no variation on the individual level). This reduced the sample by approximately one half.

Accounting for the maximum information set (preferences in D) produces on average coefficients which display a similar degree of unbiasedness. However, the underlying mechanisms and preferences are identified in a more reliable way since estimates are more efficient in terms of smaller standard errors. Figure A4.1 (in the appendix) bolsters this claim by illustrating kernel densities for the three information sets: for virtually all elements in the coefficient vectors β and γ holds that $E[\beta^I] \approx \beta^{DGP} \approx E[\beta^{II}]$ but $Var[\beta^I] < Var[\beta^{II}]$.[65]

The basic findings also hold for estimations in a simulated sample with error misspecification (normally distributed instead of type 1 extreme value), as presented in Table A4.3 and Figure A4.2 (in the appendix): more complete information sets increase the estimates' efficiency. Regarding estimates' bias, a noteworthy difference emerges in the case of an error misspecification: bias for both richer information sets is substantial for all non-zero parameters in the main DGP. Whereas misspecification in the error still allows uncovering possible decision-relevant factors, their actual impact cannot be plausibly inferred.

In reference to this small simulation study, two main conclusions can be drawn:[66] first, only conditioning on the complete space of potentially considered alternatives (the D-space) may yield unbiased estimates. A sole analysis of choices in a subsequently supply side restricted space of alternatives (the A-space) will not depict underlying mechanisms in the destination selection process in a reliable manner. Instead, substantial bias will arise almost by design. The second finding refers to the efficiency of estimated coefficients: Accounting for additional information provided by survey respondents, such as reported alternatives that were explicitly considered but eventually not selected, may enhance estimates' efficiency substantially. However, there is an interesting trade-off between analysing stated preferences and choices in the D-space. Depending on the dimensionality of the destination space and the number of stated alternatives, computational challenges might arise for the analysis of preferences. Avoiding these, and turning to an examination of choices in the destination space still yields unbiased estimates, although the corresponding test statistics will be much more conservative.

In either case, all paths in the unrestricted destination space that might have been considered, but eventually not chosen, enrich the information set such that estimations relying on individual-specific elasticities become more informative and reliable.

4.5 Empirical Results

Drawing on the findings from the Monte-Carlo simulation study, Chapter 4.5.1 presents estimation results for the corresponding empirical specifications using survey data. After demonstrating the congruence between models in the simulation and the econometric analysis, the main results based on the information sets in the D-space are discussed in more detail in Chapter 4.5.2. In Chapter 4.5.3 some tests regarding violations of the IIA are performed, and Chapter 4.5.4 introduces a framework to tackle a potential violation of the IIA.

[65] respectively $E[\gamma^I] \approx \gamma^{DGP} \approx E[\gamma^{II}]$ and $Var[\gamma^I] < Var[\gamma^{II}]$.

[66] Another result (presented in Table A4.4 in the appendix) shows that clustered errors on the individual level do affect the estimates' reliability in this application to a limited degree.

4.5.1 On the sensitivity of estimation results for varying information sets and destination spaces

Subsequently discussed estimation results originate from conditional logit models, which vary with respect to underlying information sets and destination spaces. As a baseline specification, Table 4.3 contrasts odds ratios obtained from models relying on the same definitions of information sets that are known from the simulation.[67]

The first model column in Table 4.3 refers to preferences in the destination-space ('preferences in D'), explaining the selection of the three most preferred alternatives at the application stage and the final outcome in the full set of all D potential alternatives. The second model ('choice in D') evaluates exclusively the finally observed choice in the context of the same destination space. Whereas the last model relates to the exogenously restricted choice set at the admission stage, including only these individuals who eventually had at least two alternatives with admission ('choice in A'). The explanatory variables contained in the vectors of location-specific (x_{il}, x_l) and individual characteristics (v_i), as well as some related descriptive statistics, are documented in Table A4.2.

As conjectured by the simulation study, the model estimating only choices among alternatives with admission ('choice in A', Table 4.3) displays some conspicuous features: odds ratios above (below) one are typically distinctly larger (smaller) than those in the two other models. This reflects the pronounced levels of bias in coefficient estimates observed in the simulation study. The second noteworthy aspect is a markedly differing pattern of significance. Distance, for one, is not identified as affecting destination choice significantly, the same holds for previous mobility experiences and some other socio-demographic factors. At the same time, women seemingly have significantly lower odds of choosing a destination at a certain distance than men do. One might object that this was driven by differing samples, i.e., the restricted sample comprises only 1139 instead of 1712 individuals. Yet, if the models in the complete destination space D are re-estimated for the same restricted sample as a robustness check (Table A4.7), exactly the same divergence occurs. In fact, the reason is not the sample restriction but the ignored information content in the restricted information set. This has a direct implication for analyses of location choices in a scenario with supply side restrictions: if the analyst conditions only on the subset of feasible alternatives, remaining after the completion of the admission procedure, results with respect to behaviour shaping preferences are hardly reliable in a conditional logit model.

Turning to the two models investigating preferences and choices in the complete destination space $(D = 164)$, a high degree of congruence emerges. Typically, if one model attributes a factor explanatory power, the other does, too. At the same time, coefficient estimates are slightly larger in absolute size for 'choice in D', producing odds ratios that are more different from one. There is also some evidence that some factors may play a role of varying importance within the process of

[67] Odds ratios are reported for a more immediate interpretability of results. They indicate by how much the odds of one alternative to be chosen increase (decrease) if an explanatory variable changes by one unit. Referring to the 'choice in D' (Table 4.3), for example, if two alternatives at 100 and 101 kilometres distance are compared (and everything else is held constant), the odds that the second alternative is chosen are 0.9695 times smaller than for the closer alternative. Odds ratios are directly linked to coefficient estimates, since they are calculated as $OR = e^{\beta}$, thus all essential information is preserved. Standard errors are transformed accordingly.

selecting a study location. During the application process, individuals have seemingly a certain tendency to also apply at institutions at locations characterised by lower GDP per capita and higher price levels.

Table 4.3: Conditional logit models for varying information sets

dependent variable		preferences in D		choice in D		choice in A	
observed location choices		$S \leq 4$		$S = 1$		$S = 1$	
destination space		$D = 164$		$D = 164$		$A \in [2,4]$	
		OR	s.e.	OR	s.e.	OR	s.e.
x_{il}							
distance		0.9830***	(0.0043)	0.9695***	(0.0060)	1.0014	(0.0154)
x_l							
population		1.0015***	(0.0001)	1.0025***	(0.0001)	1.0012***	(0.0003)
population density		0.9986***	(0.0001)	0.9961***	(0.0001)	0.9949***	(0.0004)
GDP (per capita)		0.9939***	(0.0018)	1.0138***	(0.0019)	1.0053	(0.0151)
price level (€/sq.)		1.0013***	(0.0002)	0.9971***	(0.0003)	1.0000	(0.0014)
share of recreational area		1.1764***	(0.0115)	1.3074***	(0.0183)	1.3344***	(0.0523)
reg. centre reachability		0.9505***	(0.0021)	0.9187***	(0.0044)	0.9173***	(0.0193)
unemployment rate		1.1563***	(0.0205)	1.0542*	(0.0304)	1.3762***	(0.1618)
youth unemp. rate		0.9919	(0.0175)	1.7445***	(0.0590)	2.3758***	(0.2840)
high-skilled emp. rate		0.9340***	(0.0070)	0.8468***	(0.0147)	0.5291***	(0.0459)
high-skilled emp. rate (<34)		1.0773***	(0.0030)	1.1785***	(0.0070)	1.3912***	(0.0430)
$v_i \# x_{il}$							
female		0.9990	(0.0007)	0.9992	(0.0009)	0.9950***	(0.0019)
age		1.0002	(0.0002)	0.9998	(0.0003)	0.9993	(0.0008)
uecgrade		0.9994	(0.0006)	1.0054***	(0.0009)	1.0001	(0.0017)
academic household		1.0023***	(0.0006)	1.0011	(0.0009)	1.0012	(0.0016)
in partnership		0.9981***	(0.0007)	0.9979**	(0.0009)	1.0001	(0.0018)
vocational education		0.9991	(0.0012)	0.9966**	(0.0016)	1.0017	(0.0041)
moved during school		1.0015**	(0.0007)	1.0018*	(0.0010)	0.9989	(0.0018)
exchange participation		1.0026***	(0.0007)	1.0028***	(0.0009)	1.0017	(0.0017)
stay abroad		1.0045***	(0.0007)	1.0049***	(0.0009)	1.0006	(0.0019)
risk attitude	low	0.9982**	(0.0007)	0.9982*	(0.0011)	0.9978	(0.0021)
	high	0.9999	(0.0010)	1.0011	(0.0013)	1.0022	(0.0025)
patience	low	0.9982*	(0.0010)	0.9989	(0.0012)	0.9922**	(0.0031)
	high	1.0018**	(0.0008)	1.0023**	(0.0011)	0.9979	(0.0023)
extraversion	low	0.9989	(0.0011)	0.9995	(0.0015)	0.9966	(0.0030)
	high	0.9990	(0.0008)	0.9990	(0.0010)	0.9998	(0.0021)
openness	low	0.9986	(0.0009)	0.9981*	(0.0011)	0.9943**	(0.0022)
	high	1.0017**	(0.0008)	1.0014	(0.0011)	1.0043**	(0.0019)
neuroticism	low	0.9988	(0.0010)	0.9978	(0.0014)	0.9962	(0.0031)
	high	1.0012	(0.0009)	0.9998	(0.0013)	0.9975	(0.0022)
conscientiousness	low	0.9997	(0.0008)	1.0002	(0.0010)	1.0000	(0.0022)
	high	0.9989	(0.0008)	0.9981	(0.0013)	1.0061***	(0.0022)
agreeableness	low	0.9988	(0.0009)	0.9981*	(0.0011)	1.0024	(0.0025)
	high	0.9999	(0.0008)	1.0016	(0.0011)	1.0050***	(0.0019)
adaptability	low	0.9984*	(0.0009)	0.9979*	(0.0012)	1.0045**	(0.0021)
	high	1.0025***	(0.0009)	1.0036***	(0.0011)	1.0058***	(0.0022)
importance of	low	1.0020**	(0.0008)	1.0031***	(0.0012)	1.0035*	(0.0021)
proximity to family	high	0.9985	(0.0011)	0.9993	(0.0015)	1.0026	(0.0034)
importance of	low	1.0020**	(0.0009)	1.0020	(0.0013)	1.0006	(0.0023)
proximity to friends	high	0.9981	(0.0012)	0.9998	(0.0016)	0.9989	(0.0031)
observations		$1712 \times D$		$1712 \times D$		$1139 \times \bar{A}$	
LL(0)		-21393.29		-8730.97		-1259.80	
LL		-13411.59		-4116.20		-478.13	
df		40		40		40	
Wald χ^2		6624.60		6793.91		576.39	
prob $> \chi^2$		0.0000		0.0000		0.0000	
pseudo R-squared		0.3731		0.5286		0.6205	

*** p<0.01, ** p<0.05, * p<0.1

Note: A sequential model comparison for 'preferences in D' and 'choice in D' is performed in Table A4.5 and Table A4.6, respectively. These model comparisons inform about the sensitivity of results with respect to the inclusion of additional personality traits. Standard errors are clustered at the individual level. '#' indicates interactions between distance and individual-specific characteristics. $\bar{A} \approx 3.1370$ is the average number of observed alternatives in the admission set of those 1139 individuals whose admission set included more than one alternative. The pseudo R-squared is calculated as $1 - LL/LL(0)$.

If they make their final choice, they are more likely to choose a destination offering better income perspectives and lower price levels, a hint towards the impact of budget restrictions. In addition, importance of proximity to friends seems to affect only the choice where to apply, but not where to eventually enrol. Beyond that, there is some evidence in favour of ability-related sorting. Given a location in a certain distance, individuals with weaker scholastic performance have higher odds of selecting themselves into such a location.

Another concern, beyond information sets, is the definition of the destination space D itself: it assumes that all 164 locations offering an economics programme are relevant potential destinations. This definition, however, does not distinguish between the types of institution, i.e., comprehensive university versus university of applied science. Moreover, some smaller institutions might just be complete unknown among individuals in the sample, thus the complete destination space would misrepresent their actual destination space and bias estimation results.

Acknowledging that the sample consists of only those individuals who signalled, by their observed enrolment choice, a certain preference for comprehensive universities, one robustness check addresses the first issue: the initial destination space of size $D = 164$ is restricted to included only those destinations actually hosting a public university.[68] This reduces the destination space in the initial application process to $D_U = 71$. In order to remedy the problem of a misspecification due to the inclusion of institutions no one in the sample was actually aware of, another version of the initial destination space comprises only those destinations ($D_S = 101$) which have been stated as most preferred (or finally chosen) alternatives by at least one individual in the sample. A comparison of Table 4.3 and Table A4.8 demonstrates that the estimation results are highly robust with respect to the three alternative destination space definitions. Using the complete destination space D, including all those destinations hosting any type of university offering an economics programme, does not adversely affect the results' reliability.

Another robustness check makes allowance for the general definition of economics programmes, including all programmes with a presumed substantial economic emphasis. Some of these might have a more specific focus and are not necessarily offered with the desired curriculum at all the institutions included in the destination space.[69] If someone is interested in International Management, institutions and therefore destinations offering only Business Studies are probably not valid alternatives. The highest degree of similarity, in terms of the curriculum, can be attributed to programmes labelled Business Studies and Economics and Business. At least one of these programmes is provided at those destinations, spanning the complete destination space. At the same time, these are, by far, the most frequently chosen programmes in the sample and also in the population of freshmen in the winter term 2013 (Destatis, 2014). As Table A4.9 reveals, the most noteworthy change is due to an increase of the estimates' variance: the odds ratios for individuals attributing proximity to family a low importance and those with completed vocational training are

[68] In contrast to those, which host exclusively universities of applied sciences.

[69] One example is Economic Engineering, which may indeed have a strong focus on economic content, yet it can also be a primarily technical study programme with some few courses in economics.

only significant in the full sample. Ultimately, restricting the sample to those 1391 individuals enrolled in one of the two programmes preserves the general sorting patterns.

In view of the facts delineated in this subchapter, and backed by the simulation study, the further discussion evolves primarily around specifications drawing on the full set of potential destinations D. Since the general interest of this research rests on factors influencing the final location choice, the relevant dependent variable is consequently 'choice in D'.

4.5.2 Discussion of the identified sorting patterns of prospective academics

Table 4.4 provides additional guidance regarding the preferred model specification. The table reports outcomes from Wald tests for varying parameter restrictions, and thus allows evaluating whether a more parsimonious model is nested in a reference specification. If this hypothesis cannot be rejected, the additional parameters in the richer model do not significantly improve the model and the more concise model is preferable.

The first reference model (M4) is the one from Table 4.3, the second model (M5) also accounts for plausible interactions between selected individual and economically relevant location-specific characteristics (Table A4.10). Individuals of different risk attitude or time preferences might display distinct geographic sorting patterns: less patient workers might exert less effort in the job search (DellaVigna and Paserman, 2005), and hence, less patient prospective academics might not consider future job perspectives at the stage of study location choice. On the other hand, a lower degree of risk aversion in the labour force is related to higher levels of unemployment (Pissarides, 1974), implying a more developed tolerance for being unemployed of more risk-loving individuals.

Table 4.4: Model comparison, based on Wald tests

choice in D	overall model fit			H_0: M nested in M5			H_0: M nested in M4		
	restrictions (df)	χ^2 (df)	P $> \chi^2$	restrictions (df)	χ^2 (df)	P $> \chi^2$	restrictions (df)	χ^2 (df)	P $> \chi^2$
M5 ($x_i, x_{il}, v_i\#x_{il}, v_i^s\#x_l^s$)	all (64)	6817.76	0.0000						
M4 ($x_i, x_{il}, v_i\#x_{il}$)	all (40)	6793.91	0.0000	$v_i^s\#x_l^s$ (24)	48.36	0.0023			
M3 ($x_{il}, v_i\#x_{il}$)	all (30)	1843.39	0.0000	$v_i^s\#x_l^s, x_l$ (34)	5384.64	0.0000	x_l (10)	5298.62	0.0000
M2 (x_i, x_{il})	all (11)	5923.00	0.0000	$v_i^s\#x_l^s, v_i\#x_{il}$ (53)	283.49	0.0000	$v_i\#x_{il}$ (29)	225.48	0.0000
M1 (x_{il})	all (1)	1553.63	0.0000	$v_i^s\#x_l^s, v_i\#x_{il}, x_l$ (63)	6058.14	0.0000	$v_i\#x_{il}, x_l$ (39)	6012.04	0.0000

Note: Reported Wald test statistics refer to the preferred specifications for 'choice in D' with a destination space $D = 164$. The model M5 (see second specification in Table A4.10) introduces plausible interaction terms of some destination-specific and individual-specific characteristics. The additional vector v_i^s comprises risk attitude and patience. Selected economically relevant location-specific characteristics (x_l^s) are GDP per capita, a price level proxy, (youth) unemployment rate and the high-skilled employment rate (of labour market entrants).

Testing more parsimonious specifications against the second model specification in Table 4.3 (choice in D), i.e., restricting the corresponding parameters of the vectors x_l, the interaction between distance (x_{il}) and v_i or both to be zero, each times leads to a rejection of the Null that the more parsimonious model is nested in the baseline specification M4: conditioning on individual characteristics increases the model fit distinctly. At the same time, M4 itself is not nested in M5, since the additional interaction terms' parameters have significant joint explanatory power. By introducing these interactions M5 proves to be more informative.

The odds ratios for the more copious model M5 (second model in Table A4.10[70]) confirm the results from the baseline model M4 (Table 4.3): aside from the existence of the distance deterrence effect (x_{il}), people tend to sort into destinations with a larger general population, which are at the same time not too densely populated. There is also the tendency to select those locations potentially offering higher consumption levels, since districts with higher GDP per capita or lower price levels are more likely to be chosen. While a larger share of recreational space seems to serve as attractor, higher travel time to the next regional centre works in the opposite direction, as an odds ratio below one for 'regional centre reachability' (measured in minutes) indicates.

The interaction terms between distance and individual characteristics provide the following interpretations: a destination in a given distance has an odds ratio below one, and thereby is less frequently chosen by individuals in a partnership (compared to those not in a relationship) or those with completed vocational training.

Individuals with previous mobility experience, e.g., a move during childhood or episodes abroad, display for a respective destination odds ratios above one. They are more willing to choose a study place farther away, since these previous experiences mitigate the perceived costs of mobility. Something similar can be observed for those expressing a relatively low preference for proximity to their family. The inversion of the argument, however, implies that more family-oriented prospective academics have a limited destination space, and hence fewer institutions to choose amongst.

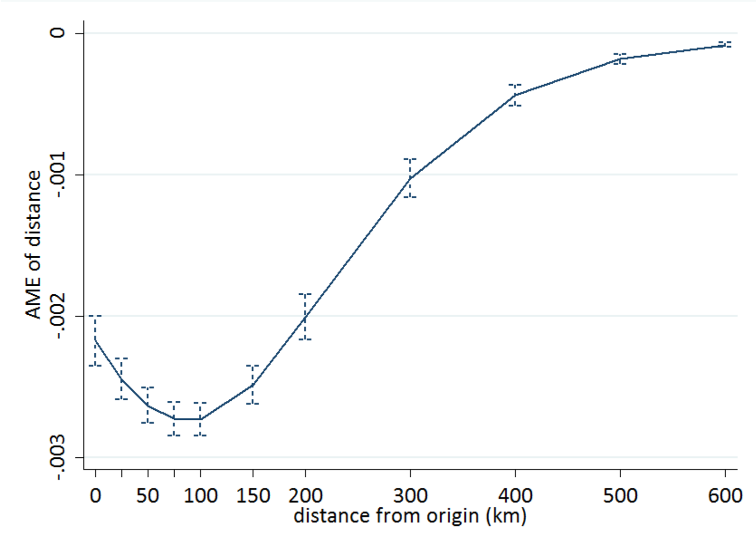
Regarding the impact of personality traits, the Big-Five do not yield robust results. Any conclusion that personality characteristics do not matter would be, nevertheless, premature: those with the lowest willingness to take risks (compared to those of average risk attitude) are distinctly less likely to sort themselves into a destination at a certain distance to their origin.

Another important and highly robust factor is individual patience – least patient prospective academics seem to be less likely to select a study location further away. Consistently, most patient individuals are characterised by a notably larger potential willingness to display mobility for educational purposes. For them, increasing returns to tertiary education, by enlarging the choice set of suitable institutions, is especially rewarding. Another relevant factor, attenuating the more immediate psychic costs of integrating into a new social and urban environment, is the ability to adjust to new circumstances. Those expressing highest (lowest) levels of adaptability have higher (lower) odds of picking an alternative at a certain distance than the reference group.

[70] This table contains also results for varying information sets and definitions of the destination space.

In order to provide a more immediate interpretation of the interaction effects of distance and location-specific conditions on the one hand and individual traits on the other, the following paragraph presents some selected graphs. Included average marginal effects and predicted choice probabilities are derived for various levels of the interacted location-specific variable within the area of support, e.g., in case of distance in the range of 0 to 600 kilometres.[71]

Figure 4.7: The decay of the distance deterrence effect – the average marginal effect of distance



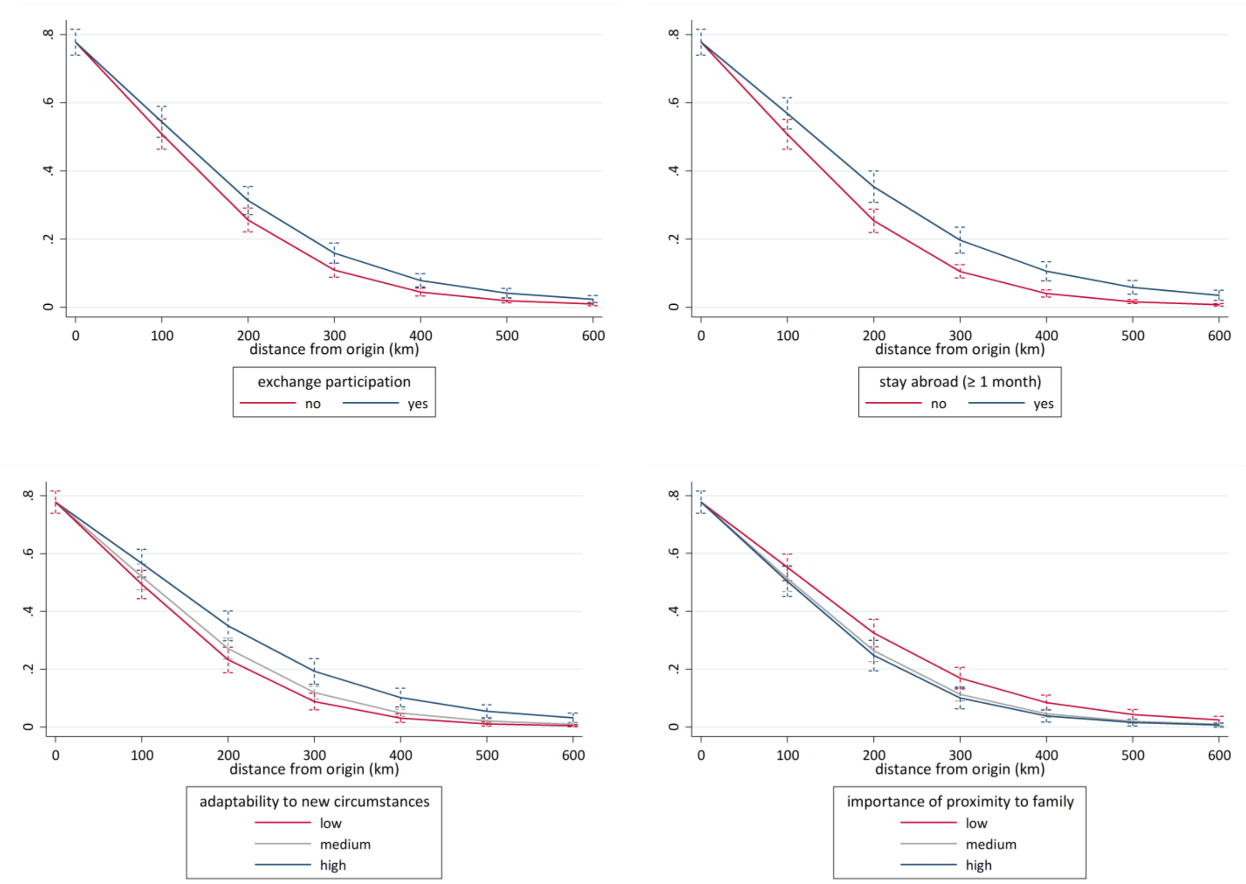
Note: The dashed whiskers indicate the 90 % confidence interval.

Figure 4.7 illustrates a diminishing distance deterrence effect for any destinations further away than 100 kilometres. Comparing two alternatives, one in 200 kilometres distance and the other (probably in another direction) 201 kilometres away, the selection probability decreases on average by 0.2 percentage points. For two locations in the vicinity of 300 kilometres distance, this effect is only half as large. This attenuating distance deterrence effect is known from the literature (Long, 2004).

In contrast to that, Figure 4.8 demonstrates that the distance deterrence effect is, in fact, related to individual characteristics. The non-overlapping confidence intervals for larger distances point to a distinct difference between individuals who have a previous mobility experience abroad and those who do not. The same holds for those with a high adaptability to new circumstances in contrast to those probably facing a harder time in a new living environment. The effect on the selection likelihood of a potential destination is rather strong: whereas most adaptable individuals feature a 20 % probability of choosing a location in 300 kilometres distance, least adaptable individuals do so with a probability of only 10 %.

[71] This range covers 99 % of all potential paths for each of the 1712 individuals in the sample to any of the 164 potential destinations.

Figure 4.8: Predicted destination selection likelihood, by various individual characteristics

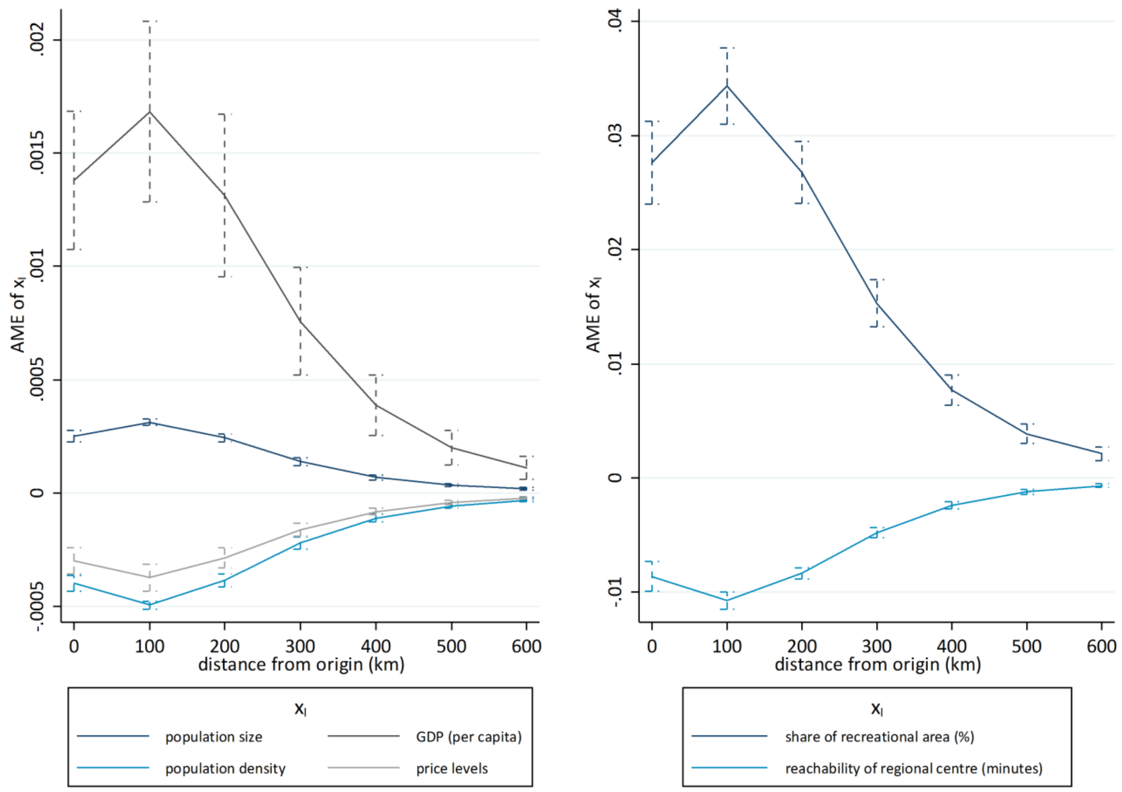


Note: The left axes represent the predicted selection likelihood of a potential destination. The dashed whiskers indicate the 90 % confidence interval.

Turning to some pivotal urban statistics (Figure 4.9), namely population size and density, gross domestic product (GDP) per capita and price levels (measured as building plot prices), observed average marginal effects are significant for all potential national destinations in a radius of up to 600 kilometres. Although many universities are situated in larger cities, negative average marginal effects of population density and price levels indicate that the subjects in the sample have a certain preference for less crowded and more affordable destinations. Prospective academics in the sample also exhibit a certain preference for destinations with higher GDP per capita, yet the interest in destinations offering higher wealth levels diminishes in distance.

The right panel in Figure 4.9 graphs average marginal effects for the share of recreational area and reachability of the closest regional centre. Both can be interpreted as factors contributing to quality of life. The first referring to a more hedonistic concept of well-being and the latter is a proxy for access to a variety of amenities which cannot be found in smaller cities (larger shopping malls, theatres or the like). Lower levels of accessibility to urban amenities are associated with a smaller destination selection likelihood. The relative impact of recreational potential is strong: if the share of the recreational area at a destination in 100 kilometres distance was to increase by one percentage point, destination selection likelihood would increase by more than 3 percentage points.

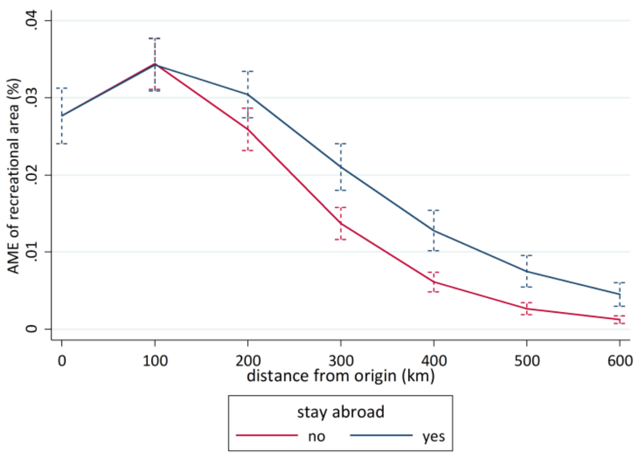
Figure 4.9: Average marginal effects of various urban characteristics over distance



Note: The dashed whiskers indicate the 90 % confidence interval.

The relevance of the hedonistic concept can also be further investigated, yielding an interesting finding (Figure 4.10). Average marginal effects across the group of those who spent time abroad and those who never made such a kind of previous mobility experience differ notably.

Figure 4.10: Average marginal effect of recreational value, by distance and previous cross-border mobility

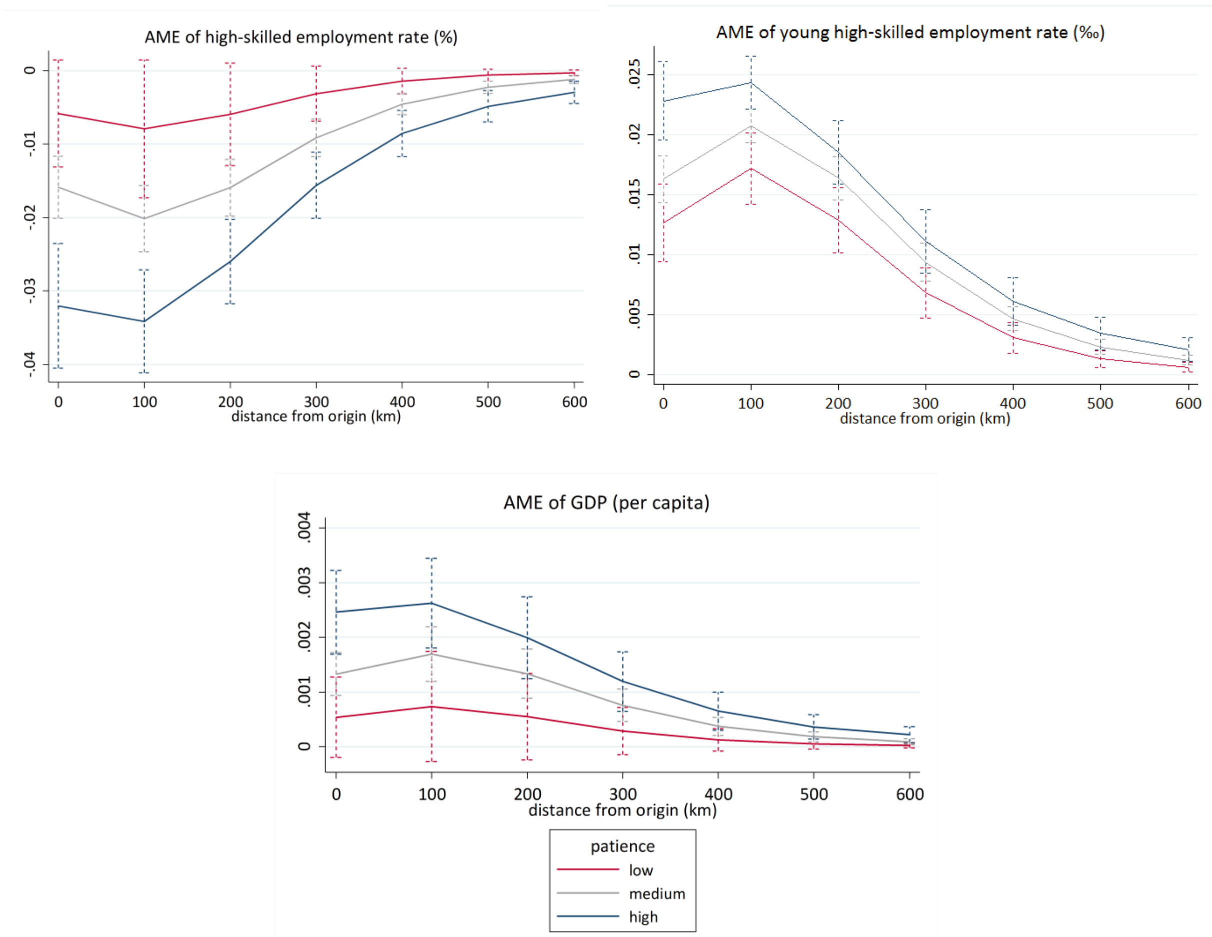


Note: The dashed whiskers indicate the 90 % confidence interval.

If the recreational area was to increase by one percentage point for a destination in 300 kilometres distance, selection likelihood increases on average by more than 2 percentage points for those who displayed this type of previous cross-border mobility. For individuals who did not make such an experience yet, the likelihood increases on average only by approximately 1.4 percentage points.

Individual-specific characteristics exert heterogeneous effects on destination choices also in the context of labour market related aspects. Especially levels of patience, corresponding to various degrees of time preferences, prove insightful (Figure 4.11). The upper left panel illustrates average marginal effects for the high-skilled employment rate at a destination, the upper right panel the corresponding graphs for the young high-skilled employment rate. The latter informs about the current job perspectives for university graduates in the age bracket of 30 to 34 years.

Figure 4.11: Average marginal effects for labour market characteristics



Note: The young high-skilled employment rate refers to employed high-skilled individuals with a university degree, aged 30 to 34, in relation to all employed and its scale is in per mille. The dashed whiskers indicate the 90 % confidence interval.

Least patient individuals display no sensitivity with respect to the age independent high-skilled employment rate (90 % confidence interval includes zero). Most patient individuals, in turn, are much less likely to choose a location with good job prospects for academics. This result is only a conundrum at first glance, since most patient individuals are much more likely to select themselves into a destination with higher employment rates of academics in their early thirties. Ultimately, these most patient individuals have a strong preference for destinations which labour markets are characterised by two features: good job perspectives for young academics who just established themselves in the labour market, on the one hand, and a not overly fierce competitive situation with older (more experienced) workers, on the other.

The lower panel reports the average marginal effect of GDP per capita. Once again, least patient individuals do not show any significant sensitivity with respect to higher income levels. Thus, the observed relevance of higher potential per capita levels (Figure 4.9) is mainly attributable to the most patient individuals.

The results highlighted in Figure 4.11 insinuate that the choice of a study location might indeed already inform about subsequent location choices, as suggested by some authors (cf. Belfield and Morris, 1999; Groen, 2004; Busch and Weigert, 2010; Buenstorf et al., 2016). This also confirms the general findings of McHugh and Morgan (1984) and Dotti et al. (2013), who elaborated that economic conditions matter already at such a pre-labour market entry stage. My results furnish a refined behavioural explanation: it is especially the most patient individuals who make in the present such distinct location decisions while keeping local post-graduation employment prospects, the future returns, in mind. Yet, even for the most patient and considerate decision-makers, distance-dependent costs of mobility are limiting the set of potential destinations and local labour markets.

Drawing on the richest model specification M5 (Table A4.10), imposing the fewest restrictions on interactions of personality or individual attributes and location-specific characteristics, this analysis demonstrated a variety of factors that attract prospective academics to a destination. Some are labour market related and others have a more hedonic implication. In most cases, however, different types of people display varying sensitivities to those factors: when it comes to the valuation of basic economic conditions or amenities, individual preferences vary substantially.

4.5.3 Testing for violations of the IIA

As previously mentioned, a relevant assumption for conditional logit estimations is the independence from irrelevant alternatives (IIA, cf. McFadden, 1973; Train, 2009). In general, this assumption follows from equation 4.2 and reads as

$$\frac{P(l|z_{il})}{P(j|z_{ij})} = \frac{\exp(z_{il}'\omega)}{\sum_{l=1}^{D}\exp(z_{il}'\omega)} \left(\frac{\exp(z_{ij}'\omega)}{\sum_{j=1}^{D}\exp\left(z_{ij}'\omega\right)}\right)^{-1} = \frac{\exp(z_{il}'\omega)}{\exp(z_{ij}'\omega)}. \tag{4.5}$$

Irrespective whether one or several alternatives (other than l and j) are added or removed from a choice set, the ratio of these two alternatives' selection probability remains unchanged. In other words, regardless of any choice set modification not affecting alternatives l and j, whenever one was preferred over the other before the change, the same holds true after the adjustment of the choice set. Moreover, if the selection likelihood of l was twice as large as the selection likelihood of j before the modification, the same must be fulfilled afterwards. In reality, however, this can be violated whenever a newly included alternative is a very close substitute to an existing one (Train, 2009).

This assumption can be tested, applying the Hausman-McFadden test (Hausman and McFadden, 1984), which basically tests the equality of coefficients obtained based on a larger choice set (D) and those resulting from a restricted choice set ($D_R \subseteq D$). If the IIA is maintained in a given model specification for a population of I individuals, the coefficient difference $\Delta = \omega_R - \omega$ should be zero, respectively converge in distribution

$$\sqrt{I}(\omega_R - \omega) \xrightarrow{d} N(0, V_R - V),$$

yielding the corresponding test statistic

$$HM = I(\omega_R - \omega)'(V_R - V)^{-1}(\omega_R - \omega).$$

Under the Null, this HM-statistic is χ^2-distributed, with the degrees of freedom equal to the rank of $V_R - V$. A rejection of the Null indicates significant differences between the coefficient vectors ω_R and ω for the corresponding model specification. An important limitation of this test, however, is given by the fact that it is rather a joint test of IIA and model-specification. It is not able to exactly distinguish between a genuine violation of the IIA and a model misspecification of some sort, i.e., in the vector z containing explanatory variables (Hausman and McFadden, 1984).

Table 4.5 reports test results for the main specifications and the relevant destination space definitions, where the unrestricted choice sets are given by D, D_U and D_S. For each of these sets, one potential destination has been excluded and a restricted version of the model has been estimated and its coefficients tested against the unrestricted model's coefficients. Then, the next alternative from the corresponding unrestricted choice set has been dropped and a new restricted model was estimated, and so on.[72] These calculations have been applied to the specifications with the maximum number of interactions (M5), the slightly restricted version comprising distance-interactions (M4) and some specifications reported in tables referring to a sequential model comparison (see Table A4.6 and Table A4.8).

Table 4.5: Hausman-McFadden test for preferred empirical specifications

destination space	observed location choices	specification	z	no H_0 rejected
$D = 164$	$S = 1$	M5	$x_i, x_{il}, v_i\#x_{il}, v_i^s\#x_l^s$	153
		M4	$x_i, x_{il}, v_i\#x_{il}$	159
		M3	$x_{il}, v_i\#x_{il}$	159
		M2	x_i, x_{il}	162
		M1	x_{il}	144
$D_U = 71$	$S = 1$	M5	$x_i, x_{il}, v_i\#x_{il}, v_i^s\#x_l^s$	67
		M4	$x_i, x_{il}, v_i\#x_{il}$	69
		M3	$x_{il}, v_i\#x_{il}$	69
		M2	x_i, x_{il}	71
		M1	x_{il}	61
$D_S = 101$	$S = 1$	M5	$x_i, x_{il}, v_i\#x_{il}, v_i^s\#x_l^s$	96
		M4	$x_i, x_{il}, v_i\#x_{il}$	99
		M3	$x_{il}, v_i\#x_{il}$	96
		M2	x_i, x_{il}	101
		M1	x_{il}	84

Note: The confidence level for the χ^2-HM test has been set to $\alpha = 0.05$. In each case, a maximum number of D (D_U or D_S) restricted models were estimated and the respective coefficients compared to those from the unrestricted model.

[72] This test has been performed using Stata's suest-command, yielding two important merits: First, it avoids the pitfall of an undefined standard Hausman test for a cluster robust variance-covariance estimator (which may not meet the test's asymptotic properties). Second, it does not rely on a fully efficient estimator for comparison, as the standard test does (cf. StataCorp, 2015).

Taken at face value, these results indicate a substantial likelihood that some of the restrictive assumptions of the conditional logit model are not met for the most preferred model specifications with the best model fit (as displayed in the previous section, Table 4.4). Yet, the distribution of estimated coefficients in the 164 restricted samples is highly concentrated around the coefficients in the unrestricted destination space (Table A4.11). In addition, the obtained estimates are in so far reliable as the number of significant parameter estimates in the restricted samples reveals. Factors that were found to be significant predictors in the unrestricted destination space retain their significant predictive power in the restricted samples.

In order to obtain some additional insights regarding potential reasons for these detected failures, applying the HM-test, I also report in Table 4.6 corresponding test results from the simulations. As a reminder, the specifications in the simulation labelled 'full' comprised only those explanatory variables which have actually been used in the simulation's data generating process. Furthermore, implemented errors satisfied the required conditions, i.e., $e_{il} \sim i.i.d.\ Gumbel(0,1)$, of a conditional logit model.

Table 4.6: Hausman-McFadden test for correct model specifications in the simulation

destination space	observed location choices	error	simulated samples	z	avg. no H_0 rejected	min. no H_0 rejected	max. no H_0 rejected
$D = 164$	$S = 1$	$\varepsilon_{il} \sim i.i.d.$ $Gumbel(0,1)$	500	$x_{il}, x_l, v_i\#x_{il}, v_i\#x_l$	159.69	154	163
$D = 164$	$S = 1$	$\varepsilon_{il} \sim i.i.d.$ $Gumbel(0,1)$	500	x_{il}, x_l	93.11	77	107

Note: The confidence level for the χ^2-HM test has been set as $\alpha = 0.05$. In each simulated sample, a maximum number of 164 restricted models were estimated and the respective coefficients compared to those from the unrestricted model.

In each of the 500 simulated samples, 159.69 HM-tests lead on average to a rejection of the Null (of equal coefficients), thus indicating a potential violation of the IIA in the model mirroring the true vector z, when a certain alternative has been excluded. In stark contrast to this, the number of average rejections declined to 93.11 for models incorporating only destination specific components into the vector of explanatory variables. Aside from the fact that this number is still very large, one has to note that the data generating process of these simulated samples was in fact based on the richer version of vector z: simulated subjects' alternative-specific utility levels of elements in the choice set have been affected (by design) by their individual preferences. Ignoring such a heterogeneous process, e.g., by stripping down vector z, would affect the individual-destination-specific errors, produce biased estimates and reduce overall model fit (as has been shown in the simulation).

As it turns out, the HM-test points in the simulation context to a reduced likelihood of a violated IIA in cases of a model actually suffering from severe misspecification. It does not seem powerful enough to provide reliable guidance in case of a complex model structure and a large choice set.

4.5.4 Heterogeneous substitution patterns in spatial choice frameworks

Although the previously applied Hausman-McFadden test proved to be insufficiently reliable in this application, a potential violation of the IIA is nevertheless a concern – the investigation of individuals' decision-making processes in such a complex context might be prone per se to such shortcomings.

An additional model extension explicitly accounts for such complex structure by acknowledging the fact that faced with a plethora of destination alternatives, a decision-maker might resort to a "hierarchical information-processing strategy where clusters of alternatives are initially evaluated before a destination is chosen from within a selected cluster" (Pellegrini and Fotheringham, 2002, p. 497). The advantage of such an information-processing based approach, compared to a nested logit model, is that it is not required to define some clusters, which were possibly never evaluated by a decision-maker.[73] Instead, a respective alternative's utility shall be weighted by the likelihood L_l that this alternative would be considered, yielding

$$P(l|z_{il}) = \frac{\exp(x_{il}'\beta + [V_i X_{il}]'\gamma) L_l}{\sum_{l=1}^{D} \exp(x_{il}'\beta + [V_i X_{il}]'\gamma) L_l}. \tag{4.6}$$

This likelihood can be modelled as a sort of average accessibility measure $A_l(D, x_l)$, which is a function of proximity to other alternatives and familiarity, the latter being driven by population size such that

$$L_l = A_l(D, x_l)^{\theta} = \left[\frac{1}{D-1} \sum_{j=1, j \neq l}^{D} \frac{pop_j}{d_{lj}}\right]^{\theta}. \tag{4.7}$$

This measure, based on Pellegrini and Fotheringham (2002) integrates, in fact, two dimensions: a form of mental accessibility relating to awareness, and the other referring to physical accessibility in the sense of Pramono and Oppewal (2012). Furthermore, this model extension yields the competing destinations model (Fotheringham, 1983; Fotheringham, 1986), where the parameter θ can be interpreted as measure regarding the level of hierarchical information processing. This modelling approach, in fact, also corresponds to a special case of the 'availability/perception' approach of Cascetta and Papola (2001) where alternatives may enter utility based on their likelihood L_{il} to be element of the resulting 'fuzzy' choice set, i.e., the consideration set: random utility is thus related to alternatives' varying degrees to be perceived or available.[74]

In the end, this modification has two interesting implications regarding the independence from irrelevant alternatives (IIA) in a spatial conditional logit model: The first merit of evaluating spatial choices in a competing destination model is an increasing chance that the IIA is not violated, since it only requires

[73] Resorting to generalised extreme value models (GEV), it is possible to relax the a priori definition of nests e.g., by using the generalised nested logit model. Introducing allocation parameters allows alternatives to be a constituent of several nests, which display varying degrees of substitutability (respectively similarity) among themselves (Hunt et al., 2004). Especially the restriction of dissimilarity parameters to be bounded between zero and one, required so the model is consistent with random utility theory, is frequently found to be violated in empirical applications. This, in turn, limits such models applicability.

[74] More precisely, this parity results for $U_{il} = z_{il}'\omega + E[\ln L_{il}] + \eta_{il} + \varepsilon_{il}$, given $\eta_{il} + \varepsilon_{il} \sim i.i.d.\, Gumbel(0,1)$.

$$\frac{P(l|z_{il})}{P(j|z_{ij})}=\frac{\exp(z_{il}'\omega)A_l^{\theta}}{\exp(z_{ij}'\omega)A_j^{\theta}}=\frac{\exp(z_{il}'\omega+\theta\ln A_l)}{\exp(z_{ij}'\omega+\theta\ln A_j)}$$

to hold. In this form, adding an alternative (hence changing the set D) with distinct characteristics is likely to change the ratio $A_l^{\theta}/A_j^{\theta}$ and thus bears the potential to accommodate observed changes in $P(l|z_{il})/P(j|z_{ij})$. At the same time, it becomes possible to test for differences in substitutability across alternatives (for $\theta \neq 0$) on the one hand, and for constant substitution patterns ($\theta = 0$). In this second case, the model would collapse into the baseline conditional logit model.

The second beneficial implication is related to the inclusion of a rich set of location-specific conditions: some destination-specific attributes, which do not only affect the selection probability of an alternative but already the likelihood that this destination is considered at all, are even controlled for in the deterministic utility component z_{il}. Consequently, it would be sufficient to include only those relationships into $A_l(D, x_l)$ which influence human information processing in a very specific way (Pellegrini and Fotheringham, 2002). One most prominent is distance-related, e.g., Sener et al. (2011) have demonstrated that for intra-metropolitan location choices possible spatial correlation can be addressed by modelling a distance-based correlation structure.

An implicit choice set modelling strategy, such as the competing destinations model entails drawbacks to be considered as well. The accessibility measure as a core component is constructed based on observed factors, thus assumes the implicit choice set formation to be deterministic itself. Moreover, inclusion into an implicit choice set is based on presumed awareness (of an alternative), and determined by spatial accessibility (Hunt et al., 2004) – though individual de facto levels of awareness, in contrast, might differ in unknown ways.

A plausible reasoning to counter such argument is to highlight actual means of gathering information. Widely available and rather detailed information about study possibilities on the internet, for instance, should foster awareness towards a finite number of potential locations: specific non-commercial information offers provide a structured overview of all possible combinations of programme and study location in Germany.[75] At the same time, spatial accessibility (also related to population size) is likely to foster a fundamental likelihood of ever having heard of a potential location – raising the likelihood of being familiar with such a possible destination.

Table 4.7 reports the results for the model specifications M2, M3 and M4 (from left to right, and one without the vector of personality variables) in the competing destinations framework, accounting for the potential violations of the IIA.

Across all specifications accounting for destination-specific conditions (x_l) in the competing destination framework, $\theta > 0$ (yielding odds ratios above one) can be observed. This implies the presence of agglomeration effects (Hunt et al., 2004), i.e., “the attraction of a cluster increases exponentially as the number of alternatives in it increases” (Pellegrini and Fotheringham, 2002, p. 500). This is not only evidence in favour of people displaying a form of hierarchical decision making,

[75] E.g., the so-called ‘Hochschulkompass’ (HRK, 2015).

but once more accentuates their overall preference for locations which are in close proximity to other alternative destinations, typically being urbanised centres: the higher the density of alternatives, respectively the more accessible it is, the more likely a specific alternative will be considered.

Table 4.7: Conditional logit results in a competing destinations framework

dependent variable		choice in D							
observed location choices		$S = 1$							
destination space		$D = 164$							
		OR	s.e.	OR	s.e.	OR	s.e.	OR	s.e.
x_{il}									
distance		0.9833***	(0.0006)	0.9709***	(0.0065)	0.9682***	(0.0062)	0.9765***	(0.0061)
x_l									
population		1.0049***	(0.0003)	1.0049***	(0.0002)			1.0048***	(0.0002)
population density		0.9936***	(0.0002)	0.9936***	(0.0002)			0.9936***	(0.0002)
GDP (per capita)		1.0490***	(0.0034)	1.0490***	(0.0034)			1.0490***	(0.0034)
price level (€/sq.)		0.9888***	(0.0005)	0.9891***	(0.0005)			0.9892***	(0.0005)
share of recreational area		1.3763***	(0.0137)	1.3824***	(0.0141)			1.3874***	(0.0143)
reg. centre reachability		0.8577***	(0.0122)	0.8616***	(0.0120)			0.8628***	(0.0121)
unemployment rate		1.6064***	(0.0742)	1.6358***	(0.0767)			1.6414***	(0.0775)
youth unemp. rate		1.7491***	(0.0825)	1.7161***	(0.0804)			1.7152***	(0.0805)
high-skilled emp. rate		0.6760***	(0.0194)	0.6773***	(0.0194)			0.6780***	(0.0193)
high-skilled emp. rate (<34)		1.3342***	(0.0157)	1.3328***	(0.0157)			1.3333***	(0.0158)
$v_i \# x_{il}$									
female				0.9991	(0.0009)	0.9994	(0.0010)	0.9989	(0.0010)
age				0.9998	(0.0003)	1.0002	(0.0003)	0.9996	(0.0003)
uecgrade				1.0062***	(0.0009)	1.0042***	(0.0009)	1.0056***	(0.0009)
academic household				1.0014	(0.0009)	1.0012	(0.0009)	1.0010	(0.0009)
in partnership				0.9979**	(0.0009)	0.9974***	(0.0010)	0.9982*	(0.0009)
vocational education				0.9944***	(0.0018)	0.9962**	(0.0017)	0.9956**	(0.0017)
moved during school				1.0024**	(0.0010)	1.0012	(0.0010)	1.0017*	(0.0010)
exchange participation				1.0028***	(0.0009)	1.0030***	(0.0009)	1.0029***	(0.0009)
stay abroad				1.0052***	(0.0010)	1.0051***	(0.0010)	1.0039***	(0.0010)
risk attitude	low					0.9985	(0.0012)	0.9982	(0.0011)
	high					1.0012	(0.0013)	1.0004	(0.0012)
patience	low					0.9988	(0.0013)	0.9989	(0.0013)
	high					1.0024**	(0.0011)	1.0030***	(0.0011)
extraversion	low					0.9981	(0.0017)	0.9999	(0.0015)
	high					0.9986	(0.0011)	0.9991	(0.0011)
openness	low					0.9985	(0.0012)	0.9977**	(0.0012)
	high					1.0006	(0.0011)	1.0007	(0.0011)
neuroticism	low					0.9981	(0.0014)	0.9977	(0.0014)
	high					1.0002	(0.0013)	0.9998	(0.0013)
conscientiousness	low					1.0006	(0.0011)	1.0003	(0.0011)
	high					0.9973*	(0.0014)	0.9978*	(0.0013)
agreeableness	low					0.9978*	(0.0012)	0.9979*	(0.0012)
	high					1.0019	(0.0012)	1.0019*	(0.0011)
adaptability	low					0.9980	(0.0014)	0.9982	(0.0013)
	high					1.0033***	(0.0011)	1.0042***	(0.0011)
importance of proximity to family	low					1.0031**	(0.0012)	1.0027**	(0.0012)
	high					0.9990	(0.0016)	0.9990	(0.0016)
importance of proximity to friends	low					1.0020	(0.0013)	1.0020	(0.0013)
	high					0.9994	(0.0017)	0.9994	(0.0017)
$\ln A_l$: accessibility of l		✓		✓		✓		✓	
observations		$1712 \times D$		$1712 \times D$		$1712 \times D$		$1712 \times D$	
LL(0)		-8730.97		-8730.97		-8730.97		-8730.97	
LL		-3836.81		-3749.59		-6477.72		-3695.04	
df		12		21		31		41	
Wald χ^2		9445.65		10159.81		1248.51		10701.20	
prob $> \chi^2$		0.0000		0.0000		0.0000		0.0000	
pseudo R-squared		0.5606		0.5705		0.2581		0.5768	

*** p<0.01, ** p<0.05, * p<0.1

Note: Standard errors are clustered at the individual level. '#' indicates interactions between distance and individual-specific characteristics. The pseudo R-squared is calculated as $1 - LL/LL(0)$. Results for alternative definitions of the destination space are reported in Table A4.12.

A negative estimate of θ results in those specifications (M3) where all parameters in the vector of destination-specific conditions have been restricted to zero. If one was to rely solely on this specification, one might conclude that alternatives in close vicinity to others would be chosen less often - the competition effect would be active. Albeit this model specification displays a much poorer model fit, as indicated by the lower log likelihood in Table 4.7 and the model selection tests in Table 4.4. Instead of the vector of location-specific conditions, the accessibility measure absorbs substantial variation.

Table 4.8: Coefficients of the accessibility measure in the competing destinations framework

destination space	observed location choices	specification	z	θ
$D = 164$	$S = 1$	M5	$x_i, x_{il}, v_i\#x_{il}, v_i^s\#x_l^s$	8.7055
		M4	$x_i, x_{il}, v_i\#x_{il}$	8.6580
		M3	$x_{il}, v_i\#x_{il}$	-1.0936
		M2	x_i, x_{il}	8.7031
$D_U = 71$	$S = 1$	M5	$x_i, x_{il}, v_i\#x_{il}, v_i^s\#x_l^s$	7.1150
		M4	$x_i, x_{il}, v_i\#x_{il}$	6.9993
		M3	$x_{il}, v_i\#x_{il}$	-0.5536
		M2	x_i, x_{il}	6.9779
$D_S = 101$	$S = 1$	M5	$x_i, x_{il}, v_i\#x_{il}, v_i^s\#x_l^s$	7.5195
		M4	$x_i, x_{il}, v_i\#x_{il}$	7.4581
		M3	$x_{il}, v_i\#x_{il}$	-0.5265
		M2	x_i, x_{il}	7.5068

Note: '#' indicates interactions between distance and individual-specific characteristics. Estimation results for M5 are not reported, the other results can be found in Table 4.7 and Table A4.12.

With respect to the previously discussed models, integrating location-specific conditions and accounting for heterogeneous effects of personality, the outcomes in the competing destinations framework support previous findings. Nevertheless, varying magnitudes of location-specific conditions' estimates illustrate a certain sensitivity of results with respect to the assumed decision-making process. The overall patterns, however, especially regarding interactions of individual personality-related and alternative-specific characteristics, remain stable in the context of a competing destinations framework, relaxing the IIA. This, in turn, promotes confidence in the core results from Chapter 4.5.1 and Chapter 4.5.2, where a possibly violated IIA assumption still advised caution.

4.6 Conclusion

This study analyses destination choices of prospectively high-skilled individuals in light of their varying preferences and personality characteristics. Moreover, I explicitly investigated the impact of choice set definition and model misspecification on estimation outcomes, both from a theoretical point of view by applying a Monte-Carlo simulation and from an empirical perspective. Individual choices have been modelled in an implicit demand and supply framework where observed choices do not solely depend on individuals' preferences, but also on an acceptance from a counterpart.

Findings from the simulation study part point to the fact that choices in a finite high-dimensional destination space are best evaluated taking the full destination space into account. All potentially relevant paths that have not been chosen, i.e., the counterfactual destinations, contain information with respect to heterogeneous preferences that can then be used in a conditional logit approach.

Accounting for heterogeneous elasticities of location-specific conditions, by introducing interactions with individual characteristics, enables tracing the impact of individual preferences and personality-related sorting patterns even in a potentially supply side restricted choice framework.

The empirical analysis investigates destination choices of students, who are homogeneous in their study preferences, but heterogeneous with respect to the perception of costs and returns of migration. The empirical random utility framework accounts for discrete location choices in presence of a plethora of alternative study locations. These 164 potential destinations offer each a distinct combination of economic and living conditions. Labour market conditions, urban characteristics (GDP per capita, population size and density) and quality of life have been shown to be relevant criteria within spatial choices of students.

The novelty of this research comes from illustrating that these conditions are valued differently across individuals displaying varying types of personality and preferences. The most patient individuals are more likely to select a location offering better post-graduation employment perspectives for high-skilled workers or higher potential income levels. The appeal of such labour market conditions, however, diminishes drastically if distance to a potential destination increases. Price levels and population density exert a deterring effect, which is also fading over distance. This implies that internal long distance migrants, who are willing to shoulder the burden of leaving their familiar environment, are less sensitive to more challenging conditions at a potential destination.

The relevance of interactions of location-specific conditions and individual characteristics has been proven to be robust, and in addition, integrating individual characteristics and preferences improved the model fit across all specifications. Moreover, the interaction of distance and personality attributes has revealed that the distance deterrence effect is not constant across an otherwise rather homogeneous population of prospective academics: perceived costs of mobility are not evenly increasing in distance, but relative to individual traits and preferences.

5 The relativity of distance: On the variation of migration outcomes in a heterogeneous general population

5.1 Introduction

Within the framework of utility-maximising decision-makers, individuals choose to relocate their centre of life whenever expected returns at least outweigh the associated costs of such a migratory event (Sjaastad, 1962). Returns can be derived from getting access to a better paid job, leading to labour mobility, or from moving to a destination offering a higher living standard. A migratory event may even result for a post-migration income below the previous level, as long as this drop is compensated by an improvement in another subjectively highly valuated dimension (Clark and Cosgrove, 1991).

In either case, individual decisions about whether to stay or to relocate are the outcome of a cognitive process, involving a subjective evaluation of available alternatives. This process can be rather complex: typically, the decision is not merely a binary one, but a plethora of alternatives may exist. Each of these alternatives offers a distinct bundle of potentially decision-relevant characteristics. Among these, distance to the current location is probably the most consistent factor, approximating the costs of migration: the larger the distance the lesser the likelihood of a destination being selected.

Yet, as decision-makers are heterogeneous, there is no plausible reason to maintain the assumption of homogeneous elasticities of selection likelihoods with respect to distance. One kilometre might not have the same deterring effect on two seemingly similar working-age individuals in a geo-referenced setup. Instead, as I will show in this concise study, distance is relative and its assessment depends crucially on individual traits.

5.2 Material and methods

5.2.1 Data sources

To assess migration-related decisions in light of individual preferences and traits, this study relies on the German Socio-Economic Panel (SOEP, version 31; cf. Wagner et al., 2007), augmented by SOEP-Geocode data. This additional data set provides information not only with respect to dichotomous stay-move decisions, but also regarding the covered distance and chosen destination. The latter is recorded on the level of regional planning units (96 RPUs in total), an intermediate spatial aggregation unit comprising several districts, yet more precise than a state-level aggregate. Even for intra-RPU moves, GPS-based distance measures implicitly provide information on the type of move: be it to a neighbouring house, another borough or another city.

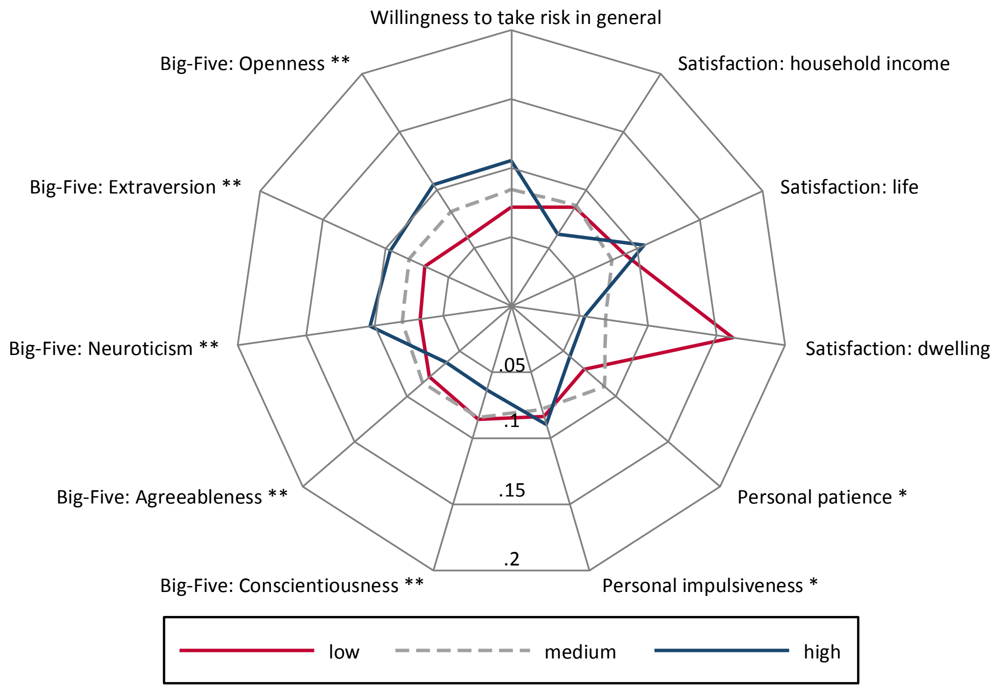
These moving distances or changes in RPU can then be linked to individual characteristics. Moreover, it is also possible to integrate destination-specific conditions acting as pull factors, e.g., by supplementing labour market data on the RPU-level from the INKAR data base (BBSR, 2016).

5.2.2 Sample definition and description

For the purpose of this study, three main requirements affect the sample definition: availability of geo-referenced data on household mobility, existence of sufficient information on individual traits and identifiability of the decision-making individual.

SOEP-Geocode data is available from 2001 onwards. Individuals' risk attitude, a highly relevant predictor of heterogeneous migratory responses (Jaeger et al., 2010) and pivotal point in this analysis, has been continuously included in the SOEP since 2008. Other potentially relevant factors, e.g., Big-Five personality traits, are less frequently available and limit, if used, the sample size notably. The third requirement constrains the sample to include only households comprising one adult person aged 18 to 64.[76] This imposed constraint enables plausible inference on the impact of individual traits, not of unobserved household bargaining processes, on migration outcomes.

Figure 5.1: Likelihood of the occurrence of a migratory event



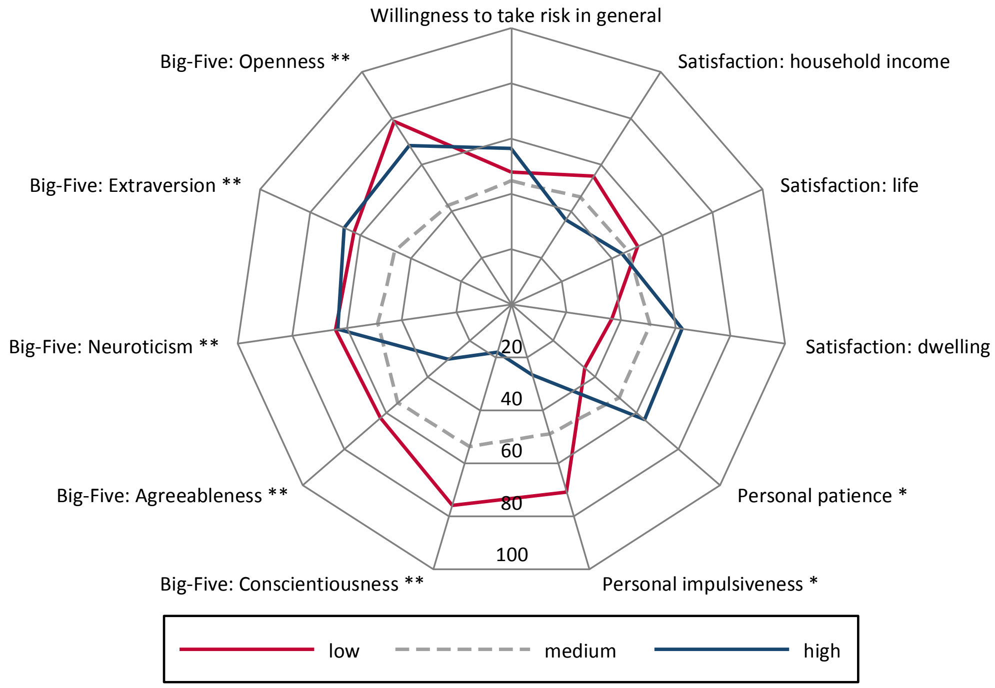
Note: * (**) indicates variables only available for 2008 and 2013 (2009 and 2013). The number of person-year observations varies across the dimensions between 3560 and 10793. The three depicted groups refer to a classification based on standardised scores, such that 'medium' refers to those scoring within one standard deviation around the mean and 'high' ('low') comprises those more than one standard deviation above (below) the mean.

Such migration outcomes y_{t+1}, occurring between the points t and $t+1$ are explained by individual traits v_{it} or destination-specific characteristics x_{lt}. This design introduces a certain degree of contemporaneous exogeneity, ensuring that the chain of causation goes from individual trait to migration outcome, not vice versa.

[76] Thus only migration decisions before the legal retirement age are considered.

Eventually, the analysed sample is an unbalanced panel (10793 person-year observations), consisting of 4044 individuals, who participated in at least two consecutive waves from 2008 to 2014 (overview in Table A5.1 in the appendix).

Figure 5.2: Average moving distance



Note: * (**) indicates variables only available for 2008 and 2013 (2009 and 2013). The number of person-year observations varies across the dimensions between 288 and 906. The three depicted groups refer to a classification based on standardised scores, such that 'medium' refers to those scoring within one standard deviation around the mean and 'high' ('low') comprises those more than one standard deviation above (below) the mean.

The potential relevance of heterogeneous individual traits and assessments for migration outcomes is sketched in Figure 5.1 and Figure 5.2. Whereas only 7.2 % of most risk-averse individuals reported a residential move, the share amounts to 10.5 % for the group of most risk-loving individuals. Conditional on the occurrence of such a migratory event, average moving distance also varies notably across groups.

5.3 Geo-referenced mobility from alternative analytical perspectives

Based on the distinct patterns briefly illustrated in Chapter 5.2.2, I address the interrelations between individual traits or valuations and various migration outcomes in three distinct analytical stages.

5.3.1 A general inclination towards mobility: The binary destination space

A natural starting point for any analysis of migration outcomes is the implicit binary destination space, essentially boiling down to either maintaining the status quo or relocating to any other location l ($y_{i,t+1}^{move} = 1$). This yields the econometric counterpart to Figure 5.1 as

$$P\left(y_{i,t+1}^{move} = 1 \middle| v_{it}\right) = \Lambda(v_{it}'\beta), \tag{5.1}$$

where $\Lambda(.)$ represents the logistic cumulative distribution, which has been chosen for reasons of a straightforward interpretation of calculated odds ratios.

The vector v_{it} consists of standard socio-demographic and socio-economic characteristics (v^{soc}), as well as labour market participation indicators (v^{lab}). Additionally, standardised information on satisfaction with life, household income and the dwelling is integrated in v^{sat};[77] standardised individual willingness to take risks acts as a pivotal personality trait across the full time horizon (2008-2013). Adding standardised Big-Five personality traits and time preference measures restricted the number of waves (2009 and 2013, respectively 2013). The cumulative sum of previously recorded moves and the total covered distance is included (v^{mob}), accounting for the concept of 'migrant personalities' (Boneva and Frieze, 2001), i.e., absorbing latent factors boosting the general inclination towards mobility or to learnt adjustment capabilities.

The selected estimation procedure is a pooled logit model with standard errors clustered on the individual level; a sequential model comparison is reported in Table A5.2. Alternative estimation strategies, i.e., random and fixed effects estimations have been explored as well (Table A5.3). Eventually, I discarded these for two reasons: first, specifications introducing relevant individual traits typically dissolve the panel structure due to an insufficient yearly coverage of relevant variables in the SOEP. This issue is even aggravated in subsequent analyses relying on smaller samples of those actually displaying residential mobility ($y_{i,t+1}^{move} = 1$). The second reason is related to this research's focus on individual characteristics affecting mobility decisions. Some of these are time-invariant, thus cannot be identified in a fixed effects (FE) specification, which is to be preferred over a comparable random effect (RE) model according to a Hausman test (Table A5.3). At the same time, the sample size decreases further, since effects of time-variant factors can only be identified for those individuals actually moving within the analysed time periods.

Table 5.1 reports some selected results for the pooled logit approach.[78] Across all specifications, future mobility becomes more likely if a person is least satisfied with the dwelling – changing the status quo is associated with relatively lower costs. Odds ratios of 2.7 and larger indicate that the odds of moving in the subsequent year are 2.7 times as large for least satisfied individuals compared to those of medium satisfaction with their dwelling.

Previous moves serve as facilitators, also increasing the general inclination towards mobility. Having one additional residential moving experience yields odds of moving once more which are 1.2 times as large as for those lacking such additional moving experience.

Introducing a richer set of personality traits reveals that the most risk-averse or least patient individuals are distinctly less likely to move, as implied by odds substantially below one: future returns to mobility will be perceived as more uncertain and weighted less than immediate mobility-

[77] Satisfaction with the dwelling is a major determinant of residential mobility (Deane, 1990).
[78] Complete results are documented in Table A5.2 (in the appendix).

related costs. On the other hand, individuals scoring highest in the Big-Five trait neuroticism are much more likely to become movers.

Table 5.1: The impact of individual traits in the binary decision space

dependent variable			$y_{i,t+1}^{move}$			
model			pooled logit			
			OR	s.e.	OR	s.e.
v_i^{sat}	overall life	low	1.0640	(0.1215)	0.6635	(0.2252)
		high	1.3972***	(0.1625)	1.1609	(0.3778)
	HH income	low	0.8047*	(0.0923)	1.0785	(0.3440)
		high	0.7547*	(0.1139)	0.9976	(0.3586)
	dwelling	low	2.7685***	(0.2383)	3.4645***	(0.7944)
		high	0.8063	(0.1193)	0.9721	(0.3817)
v_i^{mob}	previous moves		1.2180***	(0.0372)	1.2131**	(0.0919)
	covered distance		1.0003	(0.0002)	0.9998	(0.0006)
v_i^{pers}	risk attitude	low	0.9721	(0.0939)	0.3810***	(0.1257)
		high	1.1570	(0.1314)	1.0828	(0.2985)
	patience	low			0.4963**	(0.1574)
		high			0.9018	(0.2798)
	B5: openness	low			0.6442	(0.2032)
		high			0.8187	(0.2113)
	B5: extraversion	low			1.0713	(0.2988)
		high			0.9816	(0.2890)
	B5: neuroticism	low			1.0863	(0.3223)
		high			1.8482**	(0.5181)
	B5: conscientiousness	low			0.7690	(0.2201)
		high			0.8132	(0.3031)
	B5: agreeableness	low			1.0885	(0.2948)
		high			0.7289	(0.2618)
socio-demographic controls			✓		✓	
labour market controls			✓		✓	
reference years			2008 - 2013		2013	
individuals			4044		1791	
individual-year observations			10793		1791	

Note: Complete results in Table A5.2 (appendix). Odds ratios (OR) for 'high' or 'low' categories are in reference to the baseline category of 'medium-type' individuals.

5.3.2 Heterogeneous (psychic) costs of mobility: The relativity of distance-related costs

Whilst any change in the locational status quo is associated with certain costs, these costs vary with distance. The longer the covered distance, the higher travel and transportation cost will be. Aside from this direct monetary aspect, distance may also inflate psychic costs, i.e., by making it more time-consuming (or harder) to maintain social connections. Higher migratory distances also increase the likelihood of settling in an administrative or culturally different area, imposing foreseeable additional challenges to the adjustment process.[79] To establish a connection between covered distance and personality types, thus testing for heterogeneous effects of distance on migration outcomes, the following pooled log-linear model is estimated

$$\log\left(y_{i,t+1}^{dist} | y_{i,t+1}^{move} = 1\right) = v_{it}'\beta + \varepsilon_{it} \tag{5.2}$$

Since this analysis is conditional on being a residential mover, the sample size decreases drastically. In the sample of movers remain eventually 665 individuals (85.7 %) who moved only once between 2008 and 2013. 12 % moved twice and 2.3 % moved three times at least.

Conditional to being a mover, those least satisfied with their life tend to select themselves into more distant locations: on average, one would expect them to choose a destination 44 % farther away

[79] The cultural aspect is also relevant for Germany though, at first glance, being a culturally homogeneous country (Bauernschuster et al., 2014).

than a similar individual in the reference group would do (Table 5.2). The same holds for those with larger quantitative previous mobility experience (covered distance) or those least willing to take risk. Once having decided on changing the locational status quo, moving further and thus enlarging the set of potential destinations becomes more beneficial for these individuals.

Table 5.2: The interrelation between individual traits and migratory distance

dependent variable			$\log(y_{i,t+1}^{dist} \mid y_{i,t+1}^{move} = 1)$	
model			pooled OLS	
			coeff.	s.e.
v_i^{sat}	satisfaction with			
	overall life	low	0.4413*	(0.2263)
		high	-0.1171	(0.2394)
	HH income	low	0.4539*	(0.2714)
		high	-0.0905	(0.2803)
v_i^{mob}	previous moves		-0.0282	(0.0551)
	covered distance		0.0024***	(0.0005)
v_i^{pers}	risk attitude	low	0.3735*	(0.2046)
	risk attitude	high	0.4158	(0.2568)
socio-demographic controls			✓	
labour market controls			✓	
reference years			2008 – 2013	
individuals			776	
individual-year observations			907	

Note: Complete results are depicted in specification (4) in Table A5.4 (appendix). Coefficients for ‘high’ or ‘low’ categories are in reference to the baseline category of ‘medium-type’ individuals.

5.3.3 Integrating heterogeneous costs of mobility into a high-dimensional destination space

In reality, however, the world offers not only two but a plethora of alternatives. In this study’s framework, individuals can choose amongst $D = 96$ potential destinations, all of them characterised by unique features x_{lt} and different distances to an individual’s current residence.[80] Applying a conditional logit model enables controlling for destination-specific characteristics, which serve as attractors and may affect a location’s probability to be selected. In the underlying random utility model, the probability that alternative l yields a higher utility than all other potential destinations in D is given by

$$P\left(l_{t+1} \middle| y_{i,t+1}^{move} = 1, z_{ilt}\right) = P(z_{ilt}'\omega + \varepsilon_{ilt} > z_{ijt}'\omega + \varepsilon_{ijt}, \forall\, j \in D | j \neq l\,). \qquad (5.3)$$

Further assuming that errors are i.i.d. extreme value (type I), one can reformulate the selection probability of alternative l as

$$P\left(l_{t+1} \middle| y_{i,t+1}^{move} = 1, z_{ilt}\right) = \frac{\exp(z_{ilt}'\omega)}{\sum_{l=1}^{D} \exp(z_{ilt}'\omega)}\,. \qquad (5.4)$$

Two potential limitations emerge: the first refers to the model’s capability to integrate individual-specific characteristics. Assuming that vector z_{ilt} contains destination-specific variables x_{lt}, individual-specific variables v_{it} and some interactions as matrix product, equation 5.4 can be rewritten as

$$P\left(l_{t+1} \middle| y_{i,t+1}^{move} = 1, x_{ilt}, v_{it}\right) = \frac{\exp(v_{it}'\alpha)\exp(x_{ilt}'\beta + [v_{it}x_{ilt}]'\gamma)}{\exp(v_{it}'\alpha)\sum_{l=1}^{D}\exp(x_{ilt}'\beta + [v_{it}x_{ilt}]'\gamma)} = \frac{\exp(x_{ilt}'\beta + [v_{it}x_{ilt}]'\gamma)}{\sum_{l=1}^{D}\exp(x_{ilt}'\beta + [v_{it}x_{ilt}]'\gamma)}\,. \qquad (5.4')$$

[80] Distance is calculated as distance between two RPUs centroids.

All (individual) characteristics that are constant across alternatives, cancel out and corresponding parameters cannot be identified. In order to assess heterogeneous elasticities of individual traits, interactions between these traits and alternative-specific features have to be incorporated.

The second limitation originates from the underlying assumption of identical degrees of substitutability between alternatives. Whether a third alternative is added or removed from an individual's choice set is not supposed to affect the relative selection likelihood of the two other alternatives, since $P(l_{t+1}|z_{ilt})/P(j_{t+1}|z_{ijt})$ is unaffected. In spatial applications, however, this ratio tends to change, depending on the choice set.

If individuals apply some sort of hierarchical information-processing strategy, this issue can be mitigated (Pellegrini and Fotheringham, 2002): alternatives might be associated with different likelihoods to be considered at all, depending on their (mental) accessibility, which is specified as

$$A_{lt} = \left[\frac{1}{D-1}\sum_{j=1,l\neq j}^{D}\frac{population_{jt}}{distance_{lj}}\right]. \tag{5.5}$$

Accounting for such a mental process yields a modified relative selection likelihood

$$\frac{P(l_{t+1}|z_{ilt})}{P(j_{t+1}|z_{ijt})} = \frac{\exp(z'_{ilt}\omega)A_{lt}^{\theta}}{\exp(z'_{ijt}\omega)A_{jt}^{\theta}} = \frac{\exp(z'_{ilt}\omega+\theta\ln A_{lt})}{\exp(z'_{ijt}\omega+\theta\ln A_{jt})},$$

which accommodates observed changes, related to alterations of choice sets, via changes in relative accessibilities.

Table 5.3 reports results from the conditional logit model.[81] The first specification accounts solely for destination-specific characteristics (x_l) and distance (x_{il}). The second and preferred model introduces interactions between distance and the full set of individual traits (v_i), offering an interpretation as heterogeneous costs of migration in this framework. Another set of interactions between destination-specific unemployment rates and shares of employees with university degree (a proxy for knowledge clusters) and the personality trait 'risk attitude' provides insights regarding trait-specific sorting patterns into distinct regional labour markets, possibly offering differing expected returns.

Irrespective of individual characteristics, the distance deterrence effect emerges: if a considered alternative was one kilometre further away, the odds of being selected are 0.9898 times as small as for a reference destination. Ultimately, the selection likelihood of any potential destination decreases with distance to an individual's current centre of life. A further reduced selection likelihood can also be observed for older individuals, households with a higher number of children and a higher GDP per capita at a potential destination. Considering that regions with higher per capita wealth levels also exhibit higher price levels, this result becomes plausible: whilst it is not guaranteed that someone can actually benefit from such favourable income perspectives in one specific destination, the individual would nevertheless face higher local prices. More populated

[81] Model comparisons and results from the hierarchical information processing specifications are documented in Table A5.5. Results are robust with respect to the inclusion of the information processing control.

destinations are typically preferred, yielding evidence in favour of a distinct preference for more urbanised destinations.

Table 5.3: Heterogeneous selection probabilities in a high-dimensional destination space

dependent variable			$I(l_{t+1} \mid y_{i,t+1}^{move} = 1)$			
model			pooled conditional logit			
	x		OR	s.e.	OR	s.e.
x_{il}	distance		0.9723***	(0.0017)	0.9898**	(0.0052)
x_l	population (in 1000)		1.0005***	(0.0001)	1.0006***	(0.0001)
	population density		1.0002	(0.0002)	1.0002	(0.0002)
	GDP per capita (1000 €)		0.9820*	(0.0106)	0.9735**	(0.0105)
	share of recr. area		0.9692	(0.0279)	0.9827	(0.0305)
x_l^U	unemployment rate		1.0148	(0.0276)	1.0199	(0.0306)
x_l^{HS}	high-skilled emp. rate		1.0392*	(0.0223)	1.0503**	(0.0247)
$v_i^{soc} \# x_{il}$	gender (female=1)				1.0077**	(0.0034)
	age (years)				0.9995***	(0.0001)
	educational attainment					
	secondary				0.9932	(0.0051)
	tertiary				1.0114***	(0.0035)
	number of kids in HH				0.9902*	(0.0053)
	HH income				1.0000	(0.0000)
	partnership				0.9963	(0.0024)
$v_i^{soc} \# x_{il}$	LM participation					
	full-time				0.9976	(0.0036)
	part-time				0.9984	(0.0032)
	unemp. experience				0.9988	(0.0008)
$v_i^{sat} \# x_{il}$	satisfaction with					
	overall life	low			1.0063	(0.0039)
		high			0.9953	(0.0031)
	HH income	low			1.0045	(0.0038)
		high			0.9954	(0.0048)
$v_i^{mob} \# x_{il}$	sum of res. moves				0.9960***	(0.0013)
	sum of covered distance				1.0000***	(0.0000)
$v_i^{pers} \# x_{il}$	risk attitude	low			1.0020	(0.0036)
		high			1.0057*	(0.0030)
$v_i^{pers} \# x_l^U$	risk attitude	low			0.8947**	(0.0480)
		high			0.9903	(0.0545)
$v_i^{pers} \# x_l^{HS}$	risk attitude	low			1.0468	(0.0344)
		high			1.0143	(0.0339)
reference years			2008-2013		2008 – 2013	
individuals			679		679	
individual-year observations $\times D$			75936		75936	

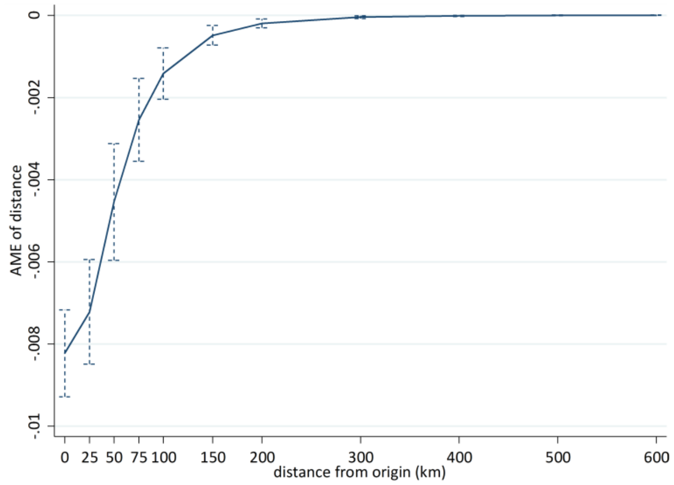
Note: Complete results are depicted in Table A5.5 (appendix, specifications 1 and 4). Odds ratios (OR) for 'high' or 'low' categories are in reference to the baseline category of 'medium-type' individuals.

For any distance, a destination is more likely to be selected by women and individuals with highest levels of educational attainment. The qualitative aspect (number of moves) and the quantitative aspect (covered distance) of past mobility experiences have diverging implications. Whereas the first lowers the selection likelihood of a destination compared to an individual with less migration experience, the second encourages it. In light of most moves being rather local moves (more than 50 % in the sample covered fewer than 5 km), larger covered distances are indicative of someone who previously made a move to an unfamiliar destination. Such an individual thus gathered experience on how to adjust to new circumstances, which in turn lowers perceived costs associated with subsequent moves.

In order to investigate the impact of complex interactions, e.g., varying effects over distance, the following graphs prove informative.

Figure 5.3 illustrates a fading distance deterrence effect: whereas any additional kilometre at 50 kilometres reduces the selection likelihood of a destination by more than 0.4 percentage points, the corresponding effect is less than half as large for a potential destination at 100 kilometres distance.

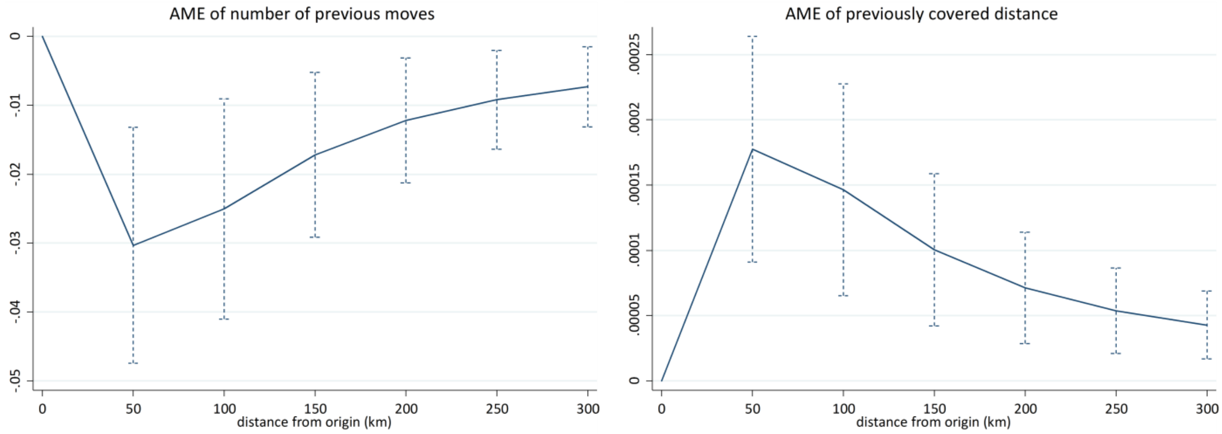
Figure 5.3: The fading distance deterrence effect - the average marginal effect of distance



Note: The dashed whiskers indicate the 90 % confidence interval.

Any additional move in the past years decreases the selection likelihood of a destination in 100 kilometres distance by around 2.5 percentage points (left panel in Figure 5.4).

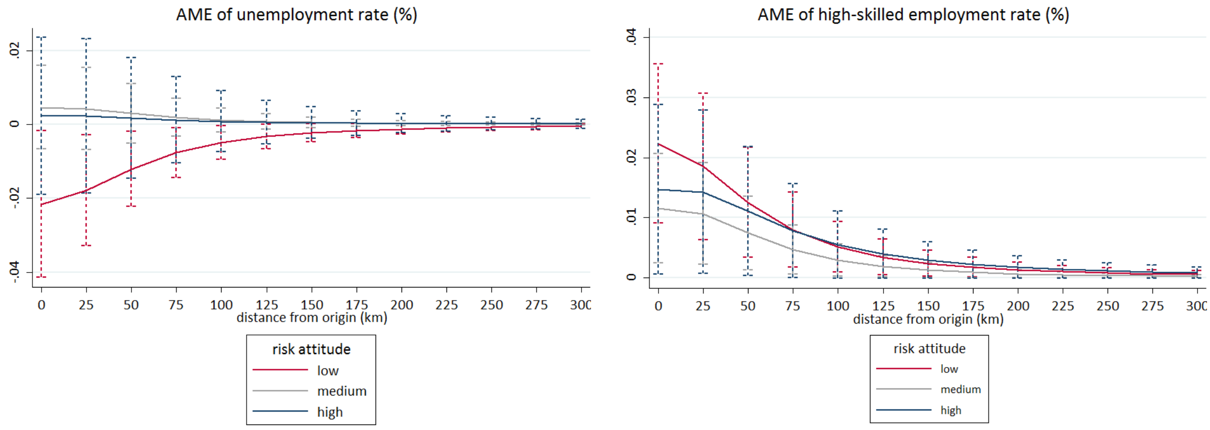
Figure 5.4: Average marginal effects of previous mobility experiences



Note: The dashed whiskers indicate the 90 % confidence interval.

Risk attitude also plays a role with respect to sorting patterns into destinations with specific labour market features. The most risk-averse individuals react more sensitively to higher levels of unemployment at a destination, indicating worse income perspectives (left panel in Figure 5.5): if the unemployment rate was one percentage point higher in one destination in 50 kilometres distance than in another comparable destination, the selection probability of the first would be 1.2 percentage points smaller. On the other hand, the same most risk-averse individuals are more likely to sort themselves into locations with a stronger knowledge base, i.e., a higher share of high-skilled employment (right panel in Figure 5.5). These trait-specific sorting patterns can be observed mainly for potential destinations in up to 150 kilometres distance. Few observation points beyond this threshold limit the possibility to derive reliable effects for larger intra-national moves in this specific sample.

Figure 5.5: Average marginal effects of labour market characteristics, conditional on risk attitude



Note: The dashed whiskers indicate the 90 % confidence interval.

5.4 Conclusion

By linking data on geo-referenced migratory events to a household panel this study points towards the existence of distinct spatial sorting patterns contingent on individual traits. People with varying characteristics and previous experiences display different location preferences. Relying on a random utility framework the preferred model specification demonstrates that the destination selection likelihood is not only affected by distance to the current location, but also depends on individual traits: the observable distance deterrence effect is individual specific. Not all individuals perceive a specific increase in distance as identically costly – the perception of distance is thus relative. Moreover, most risk-averse individuals are more reluctant to choose a destination characterised by relatively higher levels of unemployment. At the same time, these individuals have a distinct preference for knowledge cluster, i.e., regional labour markets with higher employment levels of high-skilled and a potentially more productive labour force.

As a further research angle, the analytical level of migratory events could be refined by focusing not on regional planning units as potential destinations, but on actual districts. While this does not increase the sample of mobile individuals, it clearly raises the number of distinct destinations by disaggregating the currently most frequently chosen destination, being the initial RPU of residence. This will, in turn, foster estimates' efficiency, most prominently for potential locational alternatives at short to medium distances.

6 The price of mobility: Adjustment capabilities, personality and the mobility premium of highly qualified individuals

6.1 Introduction

Since 2010, the German labour market has displayed two distinct trends, which are both interrelated with its matching efficiency. On the one hand, the average ratio of registered unemployed to job vacancies, a measure of labour market tightness, is characterised by a downward trend from 3.5 in 2010 to 3.0 in 2015. This is indicative of better job finding perspectives on the aggregate level. On the other hand, according to the Institute for Employment Research's job vacancy survey (IAB, 2016), the relative number of job hires associated with difficulties in the recruitment process increased from 29 % to 36 %. Finding a suitable employee, respectively establishing a successful job match has become more intricate.

An insufficient number of applicants was mentioned in 23 % of these difficult recruitment attempts in the year 2015, compared to 14 % in 2010. Moreover, the share of applicants with too high salary demands rose from 10 to 14 % (IAB, 2016).[82] Ultimately, locally available labour supply was declared to be insufficient – an issue more pronounced in East Germany – or there was a substantial mismatch of salary expectations.

In either case, some features in the bundle of job and regional characteristics might have been insufficient to attract applicants from another geographic labour market. In reality, such impeded geographic job mobility may occur although workers react in principle to regional labour demand differentials. Yet, job opportunities and local conditions or amenities are jointly relevant criteria when it comes to the decision whether to move to a geographically distinct labour market or not (Graves and Linneman, 1979; Roback, 1982; Clark and Cosgrove, 1991; Whisler et al., 2008; Partridge, 2010). Since the complete bundle is relevant, a lower level of amenities could in principle be compensated by a higher wage – resulting in the so-called compensating wage differential.

Referring to the introductory example of diverging salary expectations, it could be the case that a worker perceives a firm's location to be unfavourable, so he expects a substantial compensation for the associated discomfort of moving to such a location. The expected wage premium may thus be well above the remuneration package the firm is willing to offer. In a worst case scenario, such a perceived mismatch might prevent the formation of an otherwise mutually profitable employment relationship.

To prevent such an inefficient outcome, the challenge is to strike a balance between minimising the firm's labour costs and ensuring that the offered compensating wage differential is just of sufficient size to attract a suitable employee from another region (or even country). A resulting payment

[82] Other reasons, indicative of a recruitment process with difficulties, were insufficient qualification levels and a lacking willingness to accept working conditions. Multiple responses were possible.

scheme would thus not exclusively depend on expectations regarding a worker's productivity or the task profile, but also integrate a mark-up to induce mobility. In order to maintain the firm's profitability, these considerations are tantamount to the following question: What is the minimum compensating premium, ensuring that a specific qualified worker would accept this offer and move from his current location to the firm's location?

Finding an answer to this question for prospectively high-skilled workers with heterogeneous preferences and personality profiles is the first contribution of this research. This research is not limited to an analysis of observed premiums of those who chose to accept, neglecting all actually occurring salary mismatches. Instead, the overall distribution of ex ante premiums of future university graduates is investigated. Moreover, the above mentioned question will be answered for two labour market scenarios (employed vs. unemployed) and two types of mobility (interstate vs. cross-border). To the best of my knowledge, this study is also the first which explicitly integrates agents with truly heterogeneous individual traits and preferences into an analysis of compensating or post-migration wage differentials.

This study is organised as follows: Chapter 6.2 provides an overview of the literature addressing post-migration premiums, compensating or agglomeration premiums and other relevant factors shaping mobility-related decisions. In chapter 6.3, the mobility premiums are derived in a parsimonious theoretical framework, incorporating the concept of psychic costs (Sjaastad, 1962) and personality profiles. Beyond, the four alternative labour market and migration scenarios are discussed and illustrated. Chapter 6.4 delineates the data source and reveals insightful descriptive statistics. Previously derived hypothesis are then tested in the econometric analysis, performed in Chapter 6.5; sensitivity checks will supplement earlier results. Chapter 6.6 comprises the main conclusions.

6.2 Overview of the related literature

6.2.1 Mobility premiums and local conditions

Job-related migration is a predominant cause for employed men to move, but still accounts for less than one third of all migratory episodes (Böheim and Taylor, 2007). Compared to non-migrants, the average inter-district migrant or those who explicitly moved for job reasons experience a distinct real wage gain, which is not necessarily restricted to the year of migration. The wage growth rate amounts to 8 % for US interstate job-to-job changers and to 6.8 % for displaced workers (Yankow, 2003). Positive wage differentials are not only relevant for the general population of (male) employed job-changers, but they may constitute important migration incentives for unemployed (Rabe and Taylor, 2012) or foreign-born workers as well (Hall, 2009).

Especially repeat migrants seem to be able to realise highest wage gains, probably related to a successful sorting into low unemployment areas. These returns to migration seem to be increasing in educational attainment, e.g., for French labour market entrants (Lemistre and Moreau, 2009).[83] Higher education, especially, translates into additional gains, e.g., college graduates are found to receive a mobility premium for first job-related moves of around 10 % (Ham et al., 2011).[84] However, the most pronounced increase is reaped by tertiary educated, five years after the relocation (Knapp et al., 2013). Overall, higher salaries increase the probability that US college graduates will choose a more distant location (Gottlieb and Joseph, 2006). Hence, the observed mobility premium may partially act as distance compensation scheme for tertiary educated and be of substantial size too: to choose a destination twice as far, Danish scientists and engineers would expect an annual income increase of around 80 % (Dahl and Sorenson, 2010).

For Germany, Kratz and Brüderl (2013) delivered an estimate for the overall wage gain due to regional migration of 6.8 %, which comprised a contemporaneous premium of 3.7 %. With local establishment movers as control group, derived contemporaneous returns to regional migration amount to 0.4 %, and the five year premium to 1.8 % (Lehmer and Ludsteck, 2011). However, effects are heterogeneous regarding experience groups and regions: those with fewest experience realised an immediate premium of 1.8 %, which almost doubled within the subsequent five years. Leaving metropolitan areas was found to be associated with a wage decrease of 1.3 %, while departing a rural region resulted in the highest wage gains.

This finding is in line with the so-called agglomeration or urban wage differential. Moving to a metropolitan area not only leads to an upwards shift of the migrant's wage profile, but also to a persistently steeper income profile (Glaeser and Maré, 2001). Facilitated labour market coordination (better job matches) or accelerated learning process due to more frequent interactions are the likely channels.

Observing bohemian clusters in metropolitan areas, identified by the relative shares of creative minds, Florida (2002, p. 67) suggested "that a bohemian presence in an area helps establish an environment that attracts other talented or high human capital individuals". Cultural diversity, originating from heterogeneous national origins of residents, could be a production enhancing factor, making more diverse cities more attractive for native labour (Ottaviano and Pari, 2006).[85]

A large extent of the resulting urban wage premium may be related to the fact that cities attract an over proportional share of high-skilled workers (Yankow, 2006). Especially 'power-couples', where both spouses are at least college-educated, seem to be attracted to locations offering higher quality of business environment (Chen and Rosenthal, 2008). This sorting outcome might be amplified by complementarities of skills and city size (Glaeser and Resseger, 2010) – the urban income premium thus varies in relation to population size, though crowding into urban areas might also diminish returns to education (Adamson et al., 2004). Combes et al. (2008) complemented these findings by

[83] Calculated returns for women were strictly below those of their pale peers.

[84] For a subset of 12 European countries, returns to education did not vary between native stayer, native migrants and cross-border migrants (Rodríguez-Pose and Tselios, 2010).

[85] A challengeable assumption states that native workers do not vary in their taste for cultural diversity.

highlighting that skill-dependent sorting patterns of workers and employment density explain regional wage differentials also outside the metropolitan context.

The relevance of the urban wage differential is also challenged in the literature. Controlling for labour force composition and regional price differentials, including building land prices, metropolitan real wages did no longer break ranks (Blien et al., 2009). Alternatively, sorting into urban residence alongside usually unobserved family background characteristics, which are related to higher earnings potential, might bias the urban wage premium upwards (Krashinsky, 2011).

Previously described findings stress the relevance of a factor beyond mobility itself, such as local conditions at a destination. Observable income differences can then be interpreted as compensating wage differential - compensating for endowment differences between origin and destination in other relevant non-pecuniary dimensions.

One of the first links between local non-traded goods (amenities) dates back to Graves and Linneman (1979), coining the phrase 'compensating differential', which is characterised as income or rent differences to establish locational indifference. Local variations in rents or wages in a regional equilibrium thus reflect varying site-specific amenity levels (Graves, 1983). Wages in large crime-ridden cities in the US, for instance, comprise a higher compensating earnings component (Roback, 1982). The reverse was detected for climatically more favourable sites: a higher number of sunny days is associated with lower earnings. For the US, such favourable climatic conditions are robust predictors of local population growth across age-groups, and rising house prices (Rappaport, 2007) or real wages (and the hazard rate of interstate migration, cf. Huffman and Feridhanusetyawan, 2007). The presence of dis-amenities, such as emissions of toxic air pollutants, was also shown to negatively affect population growth in communities (Banzhaf and Walsh, 2008), and hence local labour supply.

Labour demand was also found to adjust to the work force's preferences. Job creation seems partially endogenous with respect to hedonic migration patterns (Kohler, 1997), pointing to a hedonic cycle: first, workers seek a location with high amenity levels. Some firms, relying on skilled labour with a distinct preference for these amenities, may then follow these workers. The resulting job creation might then attract even more workers to such a location.

Greenwood et al. (1991) challenged the regional equilibrium assumption, underlying previous studies examining compensating differentials: observed wage differentials do not exclusively capture amenity differences between locations. Clark and Cosgrove (1991) explicitly stressed the joint relevance of labour market related and hedonic migration, the first associated to labour market disequilibria and the second to households' preference for non-tradable local goods.[86] Not only do local wages reflect site-specific amenity levels, but households' willingness to migrate over a longer distance increases with the potential wage differential. Aside from economic opportunities and local

[86] Regarding mortality-adjusted population growth in Canada, Ferguson et al. (2007) elaborated that for rural areas mainly economic factors are relevant. Population growth in urban areas, in contrast, is jointly associated to economic factors and amenities, comprising natural and 'modern' (man-made) amenities.

amenities (urban characteristics, neighbourhood quality, climate, leisure and cultural offers), fiscal factors (taxes and expenditures) can also induce or deter migration, respectively (Clark and Hunter, 1992), but to varying degrees over individuals' life-cycle. Public infrastructure, such as highways, was identified as relevant household amenity too (Dalenberg and Partridge, 1997; Colombo and Stanca, 2014). Publicly provided services, e.g., education, hospitals and police, may also increase migration to a location or decrease out-migration, respectively (Clark et al., 2003). Furthermore, households' sensitivity to these services might be heterogeneous (Welch et al., 2007): whereas both tenants and homeowners seem to value police protection and libraries, other public services are mainly capitalised into either housing prices (e.g., education and roads) or rents (e.g., parks).

Job outlook, local human capital levels and population size were found to diminish outmigration (Whisler et al., 2008). Cultural and recreational offers strengthened a metropolitan area's retention capability further. The reverse was found for high costs of living. The latter was confirmed for college graduates and university graduates (Venhorst et al., 2011). Adequate job opportunities, i.e., a larger number of jobs requiring higher qualification or scientific jobs, as well as above-average regional GDP growth, were linked to lower outmigration rates. This concurs with findings that regions with universities experience in general higher in-migration rates (Biagi et al., 2011), whereas economic conditions matter primarily for long distance moves. Graduate degree holders have a preference for staying in more urban areas or where labour demand in the public sector is relatively higher (Faggian and McCann, 2009). In addition, they favour locations offering richer natural amenity levels. Negative economic shocks, such as the recession of 2007 and 2008, however, may lead to a reversal of positive skill clustering (Betz et al., 2015).

With respect to trends in US population growth Partridge (2010) contended that amenity-driven models are especially insightful. This finding might not be completely transferable to Germany, where Arntz (2010) detected only a modest overall relevance of amenities in Germany. Here, identified influential factors on migration behaviour were related to the labour market and varied by skill group: highly skilled individuals were more incentivised by interregional wage levels, less skilled individuals were more responsive to unemployment rates, and experienced higher costs of migration.

6.2.2 Individual traits and valuations affecting the migratory decision-making process

Other studies addressed the question what individual characteristics, besides socio-economic factors, might affect location preferences or location-specific earnings potentials, as well as migratory outcomes. The importance of language regarding employment perspectives and labour income has been frequently documented (e.g., Hall, 2009). Earnings of immigrants were found to be positively affected by language proficiency (Shields and Price, 2002; Dustmann and Fabbri, 2003). The latter established a positive effect on employment probability as well, though outcomes can vary distinctly by nationality. Language similarity fosters migration across borders (Adsera and Pytlikova, 2012), highlighting the mitigating effect of being familiar with a destination's language on migratory costs. Foreign language proficiency, however, not only affects cross-border migration, but commuting intentions too (Huber and Nowotny, 2013), albeit the impact lacks behind the respective impact of previous mobility experiences. Such familiarity with a culturally different setting is even relevant in a rather homogeneous country such as Germany: larger cultural distance, measured by historical dialect distance, is indicative of higher compensating post-migration wages: moving to a destination most culturally different from the origin was associated with a wage premium of around 4 % (Falck et al., 2014). Monetary measures of unobserved costs of German intrastate migration are distinctly higher and correspond to a monthly income change of € 4000, and of € 7000 for interstate migration. These costs are 31 % lower for immigrants than for natives, whereas recent immigrants face the lowest costs (Schündeln, 2014).

Valuation of amenities might be subjective, e.g., depending on educational attainment (Dalmazzo and de Blasio, 2011): individuals with highest formal education tend to report highest levels of satisfaction with amenities in the municipality, e.g., leisure activities or safety and crime control, although the provided services are objectively comparable. This underscores the likely relevance of subjective perceptions and valuations concerning location-specific opportunities within the process of migratory decision-making.

Literature also offers insights into how migration-related mental processes might pass off: individually discerned persistent dis-amenities or stressors in the accustomed environment, translating into lower levels of subjective well-being, might provoke a migratory reaction suited to provide relief. This could explain why later internal migrants, who displayed in the years before migration distinctly lower levels of happiness, managed to reach their initial levels of subjective well-being after migration (Nowok et al., 2013). In this sense, migration then serves as remedy to regain a previously higher level of well-being within the process of hedonic adaption (Graham and Oswald, 2010).

Alternatively, migratory behaviour might be "initiated and perpetuated by an ex ante aspiration gap reflecting people's desire to realise economic, social, human or political opportunities" (Czaika and Vothknecht, 2014, p. 3). Migration becomes the means of choice to close the gap between the actual and the aspired (higher) level of subjective well-being. Yet, if aspiration levels adjust themselves based on experience (Wolpert, 1965) or accordingly to aspiration adaption theory (Selten, 1998), migrants having encountered new experiences and opportunities may further raise their aspirations. Eventually, such a process could spur further migration to close the renewed aspiration gap – yielding a 'hedonic treadmill', as suggested by Czaika and Vothknecht (2014).

Personality characteristics and life events are, in this line of thought, assumed to be inputs to a 'social production function', generating subjective well-being (Ormel et al., 1999). Overall well-being comprises both physical well-being, achievable by stimulation and comfort, and social well-being, strengthened by status, behavioural confirmation and affection. Establishing a link to the compensating differential literature, moving to warmer climate could raise comfort, thus physical well-being. If only migration would provide access to a more prestigious job, social well-being would increase due to improved status.[87] Another link can be established to the distance-compensating mobility premium: if social capital depreciates over distance to its local origin, a sufficiently high premium would be required to compensate for moving to a distant labour market (David et al., 2010).

Personality traits and affective states (snapshots of well-being) are interconnected (Zautra et al., 2005), e.g., neuroticism could serve as amplifier for the consequences related to undesirable events. Furthermore, least extraverted individuals had to be more involved in desirable events to reach a comparably positive affective state than extraverted peers. Objectively comparable migration-related decisions would then affect individuals' well-being levels differently, depending on their personality characteristics: some might perceive an interstate move to be an unsurmountable hardship whilst others may view it as a welcome diversion.

The 'migration change model' partitions the mental decision-making process of a (cross-border) migrant into four distinct stages (Tabor and Milfont, 2011): the first stage (precontemplation) accounts for factors that may shape a general disposition to migrate, for instance in the sense of a 'migrant personality' (Boneva and Frieze, 2001); it captures intrapersonal factors (e.g., personality traits or risk tolerance) and familial connections. During the subsequent contemplation stage, a potential migrant weighs micro (e.g., lifestyle or employment opportunities[88]) and macro (e.g., environmental or governmental aspects) issues. The action stage is related to stress (e.g., caused by uncertainty during actual preparations) and coping mechanisms (e.g., meticulous planning and seeking for advice). The final post-migration acculturation stage involves psychological adjustment and sociocultural adaption.

Regarding migratory decision-making processes, a consistent picture emerges: internal and cross-border migrants do not base their decision purely on economic motives. Instead, their considerations include location-specific amenity levels as well. A location worth living is valued as such; any loss of well-being has to be compensated. The related wage compensation is especially relevant in case of highly educated workers, who are not only sought employees but exhibit distinct preferences for locations offering a high quality of life. These individuals, however, do differ regarding their taste and how they subjectively evaluate conditions at a potential destination. Objective facts might be rated differently: a city park of one square kilometre might be rather appealing for one person whilst another would not even consider any park smaller than New York's Central Park. Moreover, individual valuations within the assessment of potential costs and benefits related to migration will

[87] Following the reasoning of Colombo and Stanca (2014), relational amenities (time spent with friends) may have their hedonic value as well: they might lead to behavioural confirmation or affection, eventually supporting a rising level of subjective well-being.

[88] Potential migrants sometimes expressed that they expect a post-migration income loss, pointing to non-pecuniary goals of migration.

vary based on personality characteristics and aspirations. Albeit the relevance of subjective perceptions is acknowledged, literature remains silent when it comes to questions regarding the size of the mobility premium, conditional on heterogeneous individual traits.

6.3 About the nature of the mobility premium

The decision to move to an alternative location is a deliberate process, integrating over various individually relevant dimensions. Eventually, returns to mobility have at least to compensate for associated costs, such that expected utility from moving to an alternative destination D is at least equal to the expected utility from staying at the current point of origin O:

$$E[U_D] \geq E[U_O] \tag{6.1}$$

In this context, the 'mobility premium' Δ would be the minimum additional surplus related to mobility, which ensures that equation 6.1 holds. This mobility premium is highly context-specific and varies between heterogeneous agents. Yet, in any case it had to be of sufficient magnitude to tip the scale in favour of choosing the alternative location. Referring to labour migration, Δ could be a post-migration wage increase which compensates for monetary moving costs and additional costs, for instance psychic costs.[89] Here, the mobility premium was a sort of monetary incentive to induce geographically mobile behaviour, accounting also for more general preferences and accommodating non-monetary costs.

6.3.1 Modelling the mobility premium in presence of heterogeneous personality parameters

For the subsequent modelling approach I assume individuals to be partially myopic, respectively being subject to a form of bounded rationality. While life-time utility plausibly depends on all periods to come, having therefore an impact on an optimal decision in the present, human foresight is limited. Hence, an individual's decision whether to migrate or not will now be an outcome of a decision-making process referring to a limited planning horizon of only one period, representing for instance a specific stage of life. The general model design accommodates various specific types of migration: internal and cross-border migration, generic and labour mobility.

Overall utility depends on the consumption of a commodity x and availability of an amenity a_L, the latter being specific to a given location L. The consumption level of commodity x is location-specific, since it is determined by location-specific income levels I_L and prices p_L. Quality of consumption good x, however, is homogeneous across locations. This gives as modified version of equation 6.1:

$$E\left[\left(\frac{I_D}{p_D}\right)^{\alpha} a_D^{1-\alpha}\right] \geq E\left[\left(\frac{I_O}{p_O}\right)^{\alpha} a_O^{1-\alpha}\right] \tag{6.1'}$$

However, there remains a degree of uncertainty regarding location-specific labour market outcomes: with probability π_{UO}, 'bad luck' leads to job loss at the beginning of the planning horizon. This event

89 In contrast to the original idea of Sjaastad (1962) Δ is not the amount of income which could be taxed away before someone leaves a given location, but rather the minimum income gain required to ensure the willingness to move to a new location.

is exogenous from a worker's point of view, but related to local economic conditions. Individual perception of this likelihood is heterogeneous nevertheless: people do neither have perfect information on actual economic statistics nor do they evaluate available information fragments identically, thus the perceived individual job loss probability $\pi_{UO,i}$ becomes relevant.

In case of job loss, subsequent individual efforts to find new employment in location O are successful with probability $\pi_{EO,i}$. The corresponding location specific wage income w_O is assumed to be equal to the one received before. If job search remains unsuccessful, the resulting income consists of unemployment benefits $\eta_O w_O$. In the end, one obtains the expected utility for the staying option

$$E[U_O] = \left(\frac{(1-\pi_{UO,i})w_O+\pi_{UO,i}(\pi_{EO,i}w_O+(1-\pi_{EO,i})\eta_O w_O)}{p_O}\right)^{\alpha} a_O^{1-\alpha} . \tag{6.2}$$

Irrespective of an initial job loss at origin, the individual has the opportunity to look for (new) employment at alternative destinations D, resulting in 'try-your-luck' migration.[90] This endeavour is fruitful with probability $\pi_{ED,i}$, leading to a realised wage income of $w_D = w_O(1+\Delta)$, thus w_D may differ from the previous wage level at the origin. As moving would also be possible if job hunting remained unsuccessful, associated income consisted of unemployment benefits, once again calculated as replacement rate η_D times previous wage income. If origin and destination were both subject to the same legislation, i.e., in case of moving within a country, $\eta_O = \eta_D = \eta$ would result. This specification accommodates cross-border moves as well, where settling without having previously worked in a destination country would imply non-eligibility to unemployment benefits ($\eta_D = 0$).

A moving person incurs fixed expenditures Γ_D, distance dependent monetary moving costs and psychic costs, i.e., inflicted by abandoning the familiar environment. Following the idea of Schwartz (1973), the latter are incorporated as recurring costs related to the frequency of visits τ_i, required to compensate for the perceived psychic strain. This yields the distance dependent moving costs component $(1+\tau_i)f(d)$, with f being a function of distance such that $\partial f(d)/\partial d > 0$ holds.

Acculturative stress, in the context of cross-border migration (Berry et al., 1987), or challenges to the integration into a new living environment impose factors to be considered as well. Adjusting to new circumstances takes some time and may affect the ability to enjoy amenities, therefore, the subjectively perceived amenity level at a destination is $\gamma_i a_D$, with $\gamma_i \in]0,1]$. This also mirrors aspects of hedonic adaptation (Frederick and Loewenstein, 1999; Graham and Oswald, 2010), where higher levels of adaptation allow individuals to recover faster from shocks to subjective well-being, thus plausibly lowering overall perceived costs of migration-related discomfort.[91]

Taken together, these considerations yield the specification for expected utility at the destination

[90] The term is borrowed from O'Connel (1997) discussing migration under uncertainty. There, it refers to migration, which is induced by a more risky wage distribution in a potential destination whilst the actual conditions cannot be observed from the origin.

[91] Similar to Frederick and Loewenstein's (1999) prisoner example (adapting to a seven-foot cell), individuals with higher adaptability might faster adjust, e.g., to fewer recreational offers at a destination. Their overall expected change in subjective well-being would thus be smaller and require a smaller compensation or mobility premium Δ, respectively.

$$E[U_D] = \left(\frac{\pi_{ED,i}(1+\Delta)w_O + (1-\pi_{ED,i})\eta_D w_O - \Gamma_D - (1+\tau_i)f(d)}{p_D}\right)^{\alpha} (\gamma_i a_D)^{1-\alpha} \tag{6.3}$$

Substituting equations 6.2 and 6.3 into equation 6.1, and solving for the mobility premium finally results in

$$\Delta = \frac{1}{\pi_{ED,i}}\left[\left(\frac{p_D}{p_O}\right)\left(\frac{a_O}{\gamma_i a_D}\right)^{\frac{1-\alpha}{\alpha}}\left(\left(1-\pi_{UO,i}\right) + \pi_{UO,i}(\pi_{EO,i} + \left(1-\pi_{EO,i}\right)\eta_O\right) + \frac{\Gamma_D + (1+\tau_i)f(d)}{w_O} + \eta_D(\pi_{ED,i} - 1)\right] - 1. \tag{6.4}$$

Several features of the minimum premium to induce geographic mobility are apparent: relatively higher prices or lower (perceived) availability of amenities at the destination require a higher level of compensation. Generosity of unemployment benefits matters, as do costs of migration relative to previous wage levels. A higher probability of job loss is associated with a smaller premium, since the expected value of staying is diminished.[92] For there is a degree of uncertainty whether one keeps the job at the origin, a higher probability of finding new or alternative employment at a destination embodies an insurance effect, diminishing the required mobility premium.[93]

All subject-specific components (index i) in equation 6.4 are assumed to depend on individual traits or preferences. Table A6.1 (in the appendix) provides an overview over assumed interrelationships between personality parameters or personal preferences and model parameters.[94]

For instance, γ_i will be affected by individuals' adaptability to new circumstances (ϕ_A), such that $\partial\gamma_i/\partial\phi_A > 0$ holds. Beyond that, Big-Five personality traits are likely to matter as well: those more open to new experiences might be more able to benefit from amenities in a new environment ($\partial\gamma_i/\partial\psi_O > 0$). At the same time, acculturative challenges might be increasing in cultural dissimilarity (Falck et al., 2014), which is likely to become more pronounced the larger geographic distance (d) between origin and destination ($\partial\gamma_i/\partial d < 0$) or if proficiency in the local language is weak ($\partial\gamma_i/\partial\Lambda_L > 0$). This effect could be partially offset, depending on previous mobility experiences, as such experiences are indicative of enhanced inclination towards future mobility (e.g., Huber and Nowotny, 2013): someone who lived already for a certain time span abroad is likely to have developed some adjustment strategy and could thus handle unfamiliar circumstances more easily ($\partial\gamma_i/\partial\chi > 0$).

In regards to psychic costs, the required visiting frequency to compensate for psychic discomfort due to leaving the social milieu (Schwartz, 1973) is determined by individuals' extraversion and social preferences. More extraverted people are assumed to establish a new social network more easily, and thus travel back less frequently ($\partial\tau_i/\partial\psi_E < 0$). Those with closer social ties to their origin would exert more effort to maintain their connections ($\partial\tau_i/\partial\phi_S > 0$), reflecting also the idea of local social capital affecting migration outcomes (David et al., 2010).

92 For $\eta_O < 1$ it holds that $\frac{\partial\Delta}{\partial\pi_{UO,i}} = \frac{1}{\pi_{ED,i}}\left[\left(\frac{p_D}{p_O}\right)\left(\frac{a_O}{\gamma_i a_D}\right)^{\frac{1-\alpha}{\alpha}}\left(\pi_{EO,i} + \left(1-\pi_{EO,i}\right)\eta_O - 1\right)\right] < 0.$

93 Given that η_D is sufficiently small, i.e., $\eta_D < \left(\frac{p_D}{p_O}\right)\left(\frac{a_O}{\gamma_i a_D}\right)^{\frac{1-\alpha}{\alpha}}\left(\left(1-\pi_{UO,i}\right) + \pi_{UO,i}(\pi_{EO,i} + \left(1-\pi_{EO,i}\right)\eta_O\right) + \frac{\Gamma_D + (1+\tau_i)f(d)}{w_O}.$

94 Additionally, hypothetical effects on mobility premiums are denoted as well.

As initially stated, labour market related parameters are location-specific and depend on local economic conditions. Economic growth is likely to diminish the probability of a job loss. While individual performance is not supposed to affect employment adversely,[95] a more neurotic worker might still overestimate his or her individual job loss probability ($\partial\pi_{UO,i}/\partial\psi_N > 0$), which is nevertheless the relevant parameter in an individual assessment of alternatives.

On the other hand, job finding probabilities $\pi_{E,i}$ are presumed to depend on individual effort exerted during job search. Effort levels, for instance, how precisely alternatives are evaluated or how much attention is paid to an application, are supposed to be shaped by personality traits such as agreeableness (ψ_A) and conscientiousness (ψ_C). The latter has been found to be associated to a more intensive job interview preparation (Caldwell and Burger, 1998).

Risk-attitude (ϕ_R) is likely to play a role as well (Ekelund et al., 2005; Kern, 2015): more risk-loving individuals might consider self-employment as an additional alternative, increasing the overall likelihood of generating labour market income in one way or another. Furthermore, a patience parameter (ϕ_P) might also be indicative of improved job finding perspectives if this parameter refers to individual willingness to bear higher (search) costs for the sake of increasing expected deferred returns (DellaVigna and Paserman, 2005). The basic relations are thus $\partial\pi_{EL,i}/\partial\psi_C > 0$, $\partial\pi_{EL,i}/\partial\psi_A > 0$, $\partial\pi_{EL,i}/\partial\phi_R > 0$ and $\partial\pi_{EL,i}/\partial\phi_P > 0$.

Aside from personality parameters, human capital will matter too. Especially language proficiency in the local language at location L will boost employment perspectives: language proficiency may facilitate job search, help communicating own qualifications to prospective employers or be a prerequisite in occupations with customers (Dustmann and Fabbri, 2003).

Eventually, outlined channels highlight some plausible general mechanisms how personality and individual preferences might be associated with the mobility premium and consequently with migration outcomes.

6.3.2 Scenario-specific mobility premiums

Within the empirical analysis expected mobility premiums in four distinct scenarios are examined. These scenarios are defined by the likelihood of becoming unemployed and whether a cross-border move is considered or not.

1. <u>Scenario A1</u>: *internal try-your-luck migration*

   The individual can retain the work place at the origin ($\pi_{UO,i} = 0$), but considers moving to an alternative location within the same jurisdiction ($\gamma_{i1}(d_1)$, $\eta_D > 0$):

   $$\Delta_{A1,i} = \frac{1}{\pi_{ED1,i}}\left[\left(\frac{p_{D1}}{p_O}\right)\left(\frac{a_O}{\gamma_{i1}(d_1)a_{D1}}\right)^{\frac{1-\alpha}{\alpha}} + \frac{\Gamma_D+(1+\tau_i)f(d_1)}{w_O} + \eta_D(\pi_{ED1,i}-1)\right] - 1$$

[95] In extreme cases, even shirking would go unpunished. Such an outcome is not at all unrealistic in the presence of strong worker protection.

2. Scenario A2: *cross-border try-your-luck migration*

   Though having employment at the origin ($\pi_{UO,i} = 0$), the individual considers migrating to another country ($\gamma_{i2}(d_2), \eta_D = 0$):

   $$\Delta_{A2,i} = \frac{1}{\pi_{ED2,i}}\left[\left(\frac{p_{D2}}{p_O}\right)\left(\frac{a_O}{\gamma_{i2}(d_2)a_{D2}}\right)^{\frac{1-\alpha}{\alpha}} + \frac{\Gamma_D+(1+\tau_i)f(d_2)}{w_O}\right] - 1$$

3. Scenario U1: *internal migration to avoid unemployment*

   If the individual decides to stay, he will be unemployed ($\pi_{UO,i} = 1$). Hence a possible alternative to avoid an unemployment spell is to move to another district in the same country ($\gamma_{i1}(d_1)$, $\eta_O = \eta_D, \eta_O > 0$):

   $$\Delta_{U1,i} = \frac{1}{\pi_{ED1,i}}\left[\left(\frac{p_{D1}}{p_O}\right)\left(\frac{a_O}{\gamma_{i1}(d_1)a_{D1}}\right)^{\frac{1-\alpha}{\alpha}}\left(\pi_{EO,i} + \left(1-\pi_{EO,i}\right)\eta_O\right) + \frac{\Gamma_D+(1+\tau_i)f(d_1)}{w_O} + \eta_O(\pi_{ED1,i} - 1)\right] - 1$$

4. Scenario U2: *cross-border migration to avoid unemployment*

   Being without employment at the origin ($\pi_{UO,i} = 1$), the subject evaluates relocating to another country ($\gamma_{i2}(d_2)$, $\eta_O > 0, \eta_D = 0$) to find gainful employment:

   $$\Delta_{U2,i} = \frac{1}{\pi_{ED2,i}}\left[\left(\frac{p_{D2}}{p_O}\right)\left(\frac{a_O}{\gamma_{i2}(d_2)a_{D2}}\right)^{\frac{1-\alpha}{\alpha}}\left(\pi_{EO,i} + \left(1-\pi_{EO,i}\right)\eta_O\right) + \frac{\Gamma_D+(1+\tau_i)f(d_2)}{w_O}\right] - 1$$

These four depicted scenarios provide some immediate guidance regarding the magnitude or even the sign of the expected mobility premium.

Typically, the mobility premiums to induce a move abroad should be larger than those related to intra-national moves ($\Delta_{A2,i} > \Delta_{A1,i}$ and $\Delta_{U2,i} > \Delta_{U1,i}$). This difference comprises of an acculturative premium, and a compensation for the loss of unemployment insurance abroad.

For any replacement rate $\eta_O \in]0,1[$ there results an excess mobility premium ($\Delta_{A1,i} > \Delta_{U1,i}$ and $\Delta_{A2,i} > \Delta_{U2,i}$) for the employed. It compensates for a relatively higher value of staying due to having employment at the origin.

The mobility premiums can take on negative values ($\Delta_i < 0$) across scenarios if they are interpreted as hedonic premiums. This is the case whenever price levels at a destination are sufficiently below those at the origin, increasing consumption possibilities, or the subjectively perceived level of amenities at a destination is sufficiently above those at the origin. This constitutes the direct link to the compensating differential literature.

Overall, the model's parameterisation points to the relevance of location-specific (economic) conditions, respectively, to the importance of differentials between current location and potential destination. Outcomes will, thus, depend on the actual scenario a decision-maker is facing: on average, someone already residing in a rather advantageous location can be expected to ask for a higher mobility premium than someone originating from a less favourable region.

6.3.3 A general visualisation of the mobility premium

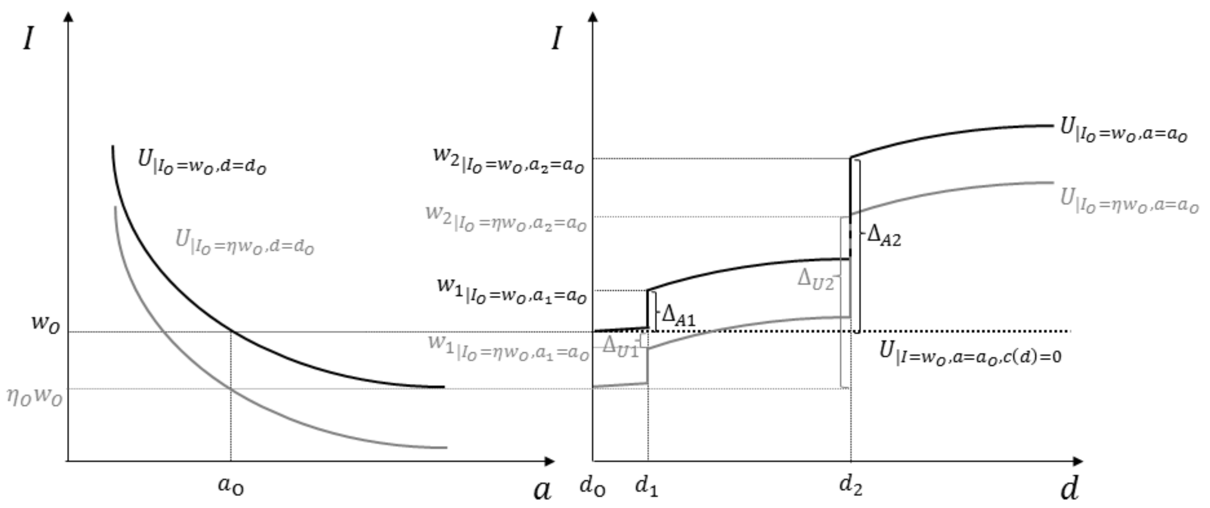
In order to provide a more graspable explanation of the interconnectedness of income, amenities, and mobility or their consequences for individual utility, Figure 6.1 portrays some basic connections.

Whereas relative individual preferences regarding consumption of (traded) goods and amenities are primarily expressed by the slope of the curve in the income-amenity space (left panel), corresponding curves in the income-distance space (right panel) capture other individual traits.[96] The latter graph can also be interpreted as graphical representation of a wage-acceptance function, which depends on distance and destination.[97]

The iso-utility curve $U_{|I_O=w_O,d=0}$ (black) in the left graph depicts all combinations of wage and amenity levels at a location (here denoted as origin), which yield the same level of utility. A representative individual is currently employed, earns labour income w_O and enjoys an amenity level of a_O. In a world without language or administrative borders, where transport would neither cost time nor money,[98] the individual would be indifferent between any location offering amenity level a_0 and earnings comparable to w_O (indicated by the horizontal dotted iso-utility curve $U_{|I=w_O,a=a_O,c(d)=0}$ in the right panel).

Since this is a rather unrealistic scenario, I assume in the following that transportation costs are increasing in distance. Additionally, the individual extracts no utility gains from setting out into the world, which could in extreme cases offset monetary costs. Consequently, the black curve $U_{|I_O=w_O,a=a_O}$ in the right panel shows for which income levels the individual would be indifferent between staying or moving to a location providing constant amenities in a certain distance d. The slope of this curve's segments indicates how associated costs of mobility are perceived by the individual: someone putting relatively heavier weight on existing social ties might experience higher psychic costs of moving to a more remote location, and thus, the slope would be more pronounced (see Figure 6.2).

Figure 6.1: Iso-utility curves in the benchmark and unemployment scenario



[96] The vertical axis refers to income, and hence it parallels the two forms of income in the model, i.e., labour income (w_O) and unemployment benefits (ηw_O). The main implications would also be preserved if the real income, also integrating prices, was considered.

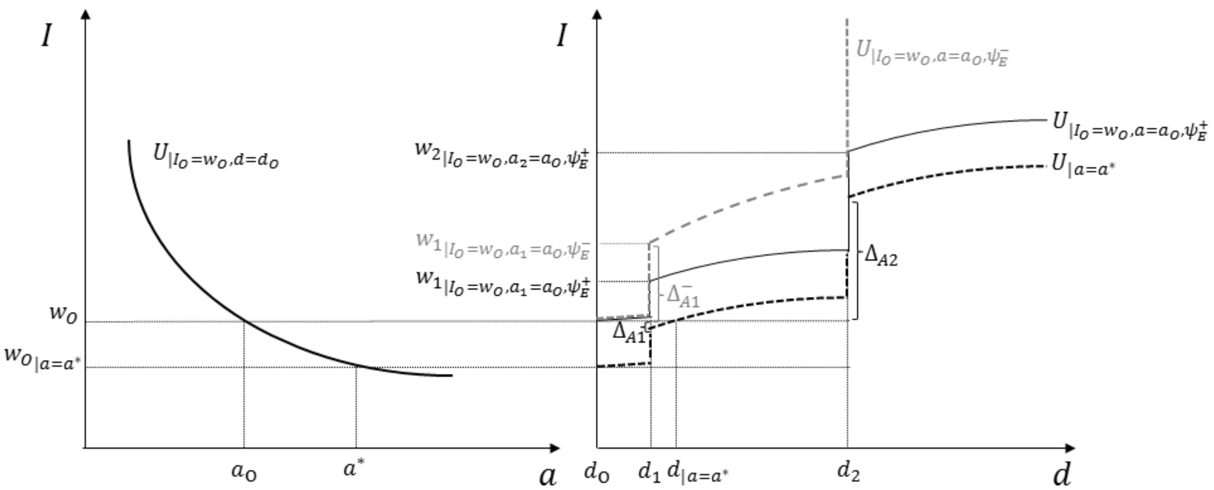
[97] Relevant destinations in this context are other states or countries. The figure in the right panel is only one possible representation among all potential paths from an origin. The thresholds d_1 (distance to the interstate border) and d_2 (distance to the national border) may vary, depending on the selected direction.

[98] This would automatically imply that psychic cost become irrelevant.

Two discontinuities can be seen: the first occurs at d_1, the second at d_2. The first jump indicates the threshold between commuting distances and distances for which the individual would choose to move, for instance, if an alternative job was in another state.[99] Because moving engenders additional costs, e.g., removal expenses or a brokerage fee, we observe this jump. The second jump indicates a distance which would require border-crossing. Here, especially costs related to language and cultural barriers or psychic costs might explain the sudden rise in 'distance-dependent' costs. The iso-utility curve of a person fluent in the neighbouring country's language might display a less marked jump than for someone who never experienced a spell abroad. Eventually, to be willing to move to any location (for $a = a_O$) just marginally beyond these thresholds, the individual under consideration would expect a compensation in form of a wage premium of at least Δ_{A1}, respectively Δ_{A2}.

In an alternative scenario, the individual experiences a job loss at home due to a local economic shock – realised income is now given by unemployment benefits ($\eta_O w_O$). Such a shock shifts the iso-utility curve in the income-amenity space downwards to $U_{|I_O=\eta w_O,\, d=d_O}$ (grey). For the 'outside-option' staying at the origin becomes now less attractive, the corresponding curve in the income-distance space shifts downwards as well. This implies that the individual was now willing to cross the threshold d_1 and move to another state if the potential destination would offer an income of $w_{1|I_O=\eta w_O, a_1=a_O}$ or more. The associated mobility premium Δ_{U1} would be negative, albeit the premium to migrate to a location in another country (and cross the threshold d_2) remained distinctly positive.

Figure 6.2: Iso-utility curves in the aspiration and personality scenario



A third exposition (Figure 6.2) dwells upon an individual who is employed, yet aspires a higher amenity level a^*, possibly related to a life-course event. Though this person would be willing to accept a lower wage ($w_{O|a=a^*}$) at the familiar environment, her current location is not endowed with the desired amenity level.

[99] For the scenarios in which commuting is required to get to work, the costs are likely to increase in distance as well. Nevertheless, monetary costs could stay constant as well, for instance, if the considered commuting distance is covered by an already acquired commuting ticket for public transport.

To maintain the familiar overall subjective well-being (represented by $U_{|I_O=w_O,d=0}$) whilst gaining access to a^*, the individual would be willing to move to any location characterised by lying on $U_{|a=a^*}$ (black dashed curve) or above in the income-distance space. For a sufficiently large difference between a^* and a_O, the mobility premium Δ_{A1} can become negative. In the event that the current (or any other) employer offered the same remuneration as at the origin, the individual could improve his or her well-being by moving to another state, as long as the destination is not farther away than $d_{|a=a^*}$.

Finally, let us consider two individuals with the same relative preferences for amenities and tradable consumption goods, purchasable with income. The first person corresponds to the benchmark individual and is an extraverted character (ψ_E^+) with iso-utility curve $U_{|I_O=w_O,a=a_O,\psi_E^+}$ (black solid curve in Figure 6.2) in the income-distance space. In contrast, the other person is introverted (ψ_E^-), featuring high psychic cost of leaving the familiar environment. This leads to more pronounced jumps at the distance thresholds and to a steeper profile over migratory distance d. As the corresponding iso-utility curve $U_{|I_O=w_O,a=a_O,\psi_E^-}$ (grey dashed curve) indicates, the mobility premium to move to another state Δ_{A1}^- is much larger than for the (extraverted) benchmark individual (Δ_{A1} in Figure 6.1). There exists at the same time no mobility premium to compensate the least extraverted person for the perceived hardship of moving to another country.

6.4 Data and descriptive statistics

Previously presented hypotheses are tested using individual microdata from a survey on “Mobility, Expectations, Self-Assessment and Risk Attitude of Students” (Weisser, 2016a). This cross-sectional survey comprises a large variety of items directly assessing individuals’ inclination towards various forms of mobility and related preferences. The survey’s target group, comprising students enrolled in an economics programme, allows addressing questions specifically related to prospectively highly educated individuals, constituting a substantial fraction of the future’s highly-skilled labour force.[100]
In addition to individual characteristics, such as personality traits and personal valuations, the survey explicitly asked for postal codes to map episodes of geographic mobility in a geo-referenced framework. This approach allows to identify individuals’ current residence, and thereby to isolate a geographic reference point to which they might compare amenity levels at a potential destination.

Having sketched the relevance of location-specific conditions in the above described model, the subsequent empirical analysis is explicitly taking these components into account. All location-specific data, e.g., economic and demographic conditions, originate from the ‘INKAR online’ database (BBSR, 2014). The chosen reference year is 2012, the most recent year before the survey took place. Extracted data furnishes information on the district level, which makes it possible to merge

[100] Using administrative data, a high degree of representativeness could be established. More information regarding data compilation or sample composition can be found in Weisser (2016b). In addition, Table A6.2 depicts descriptive statistics for all variables used in subsequent analyses.

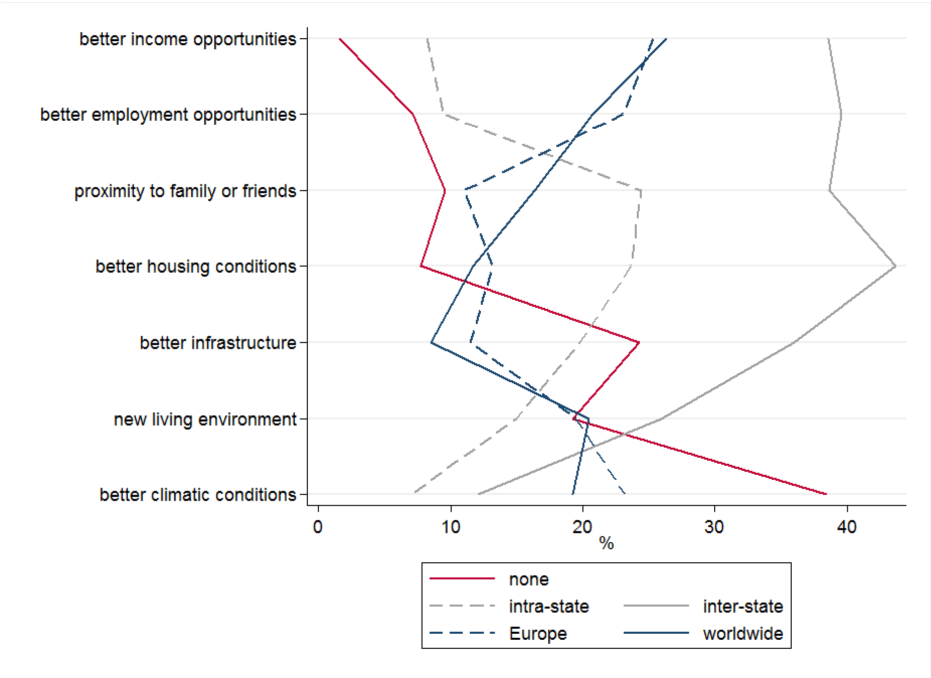
information on local circumstances with individuals' geo-referenced whereabouts. In the end it can be inferred how large GDP per capita or unemployment was in the district where a respondent resided. Referring to the amenity domain, the INKAR data even provides information on locally available recreational area or transport connections.

6.4.1 Migration motives and willingness to move

The literature review presented a variety of influential factors affecting migration. Some factors, e.g., finding new employment or improving quality of life, may act as important motives to induce different types of migration. The realisation of more pressing motives, related to a substantial increase of subjective or economic well-being, might trigger a long distance move. Finding gainful employment in case of unemployment can be such a motive. The realisation of other motives, perceived as less important, could be too costly to induce any migratory reaction at all. In either case, individual evaluations are likely to vary over the life-cycle and depend on individual preferences.

For seven different motives participants have been asked to state the maximum migratory move they would consider to realise the associated motive. The results in Figure 6.3 illustrate that especially economic motives might induce higher degrees of mobility.

Figure 6.3: Maximum willingness to move, by motive (in %)



Note: Sample size for all seven motives varies between 2202 and 2216 respondents.

However, almost 17 % explained their unwillingness to move to another state (or beyond) to improve employment opportunities in case of unemployment. Most notably, 7.2 % claim to be unwilling to move at all, even within the state. Nevertheless, cross-border moves are, to a larger extent, considered in case of labour market related motives. From an ex ante perspective, approximately

44 % mention a basic willingness to leave the country for better job opportunities (in case of unemployment) and 51.5 % state that better income opportunities would make them consider a cross-border move.

In contrast to this, prospective university graduates are less inclined to move to another country for the sake of being closer to family or friends. The same holds for gaining access to better housing conditions or infrastructure. If they strive for improvements in these dimensions, primarily intra-national moves are considered. Since most respondents in the sample have been born and raised in Germany, increasing proximity to reference persons typically does not require a cross-border move. Similarly, housing and infrastructure quality in Germany can be assumed to be relatively high, hence migrating to another country would not yield an improvement.

Climatic conditions, often identified as relevant migration motive (cf. Rappaport, 2007), do not constitute an important migration motive for young adults in this sample: 38.4 % display a complete unwillingness to move at all in order to get to a location offering better climatic conditions. The possibility to explore new living environments is for 60 % not a sufficiently strong motive to induce cross-border mobility, although especially such a move would imply immediate contact with a new cultural environment.

The observed variation in the shares of individuals willing to display a specific degree of mobility stresses the relevance of the underlying individual aspiration. Some motives seem to be more urgent than others. At the same time and across motives, a notable share of individuals - ranging from 10 % to 45 % - lacks any willingness to move beyond the intra-German state borders. Staying at or remaining close to a place of residence is highly valued. In all likelihood, offsetting such a tendency to dwell requires a substantial mobility premium, even to induce interstate mobility.

6.4.2 Distribution of mobility premiums for various scenarios and personality dimensions

The mobility premiums have been derived from items inquiring expected income levels for the four scenarios.[101] As a benchmark (w_O) served the minimum expected net income after graduation. Furthermore, expected income levels so a respondent would be willing to move to an alternative destination have been directly asked for. Being confronted with precisely depicted scenarios, participants stated their expected wage levels for internal (w_{A1}) and cross-border (w_{A2}) try-your-luck migration, respectively internal (w_{U1}) and cross-border (w_{U2}) migration to avoid unemployment. Accordingly, one obtains as mobility premium, e.g., in case of cross-border mobility in the unemployment scenario:

$$\Delta_{U2} = \frac{w_{U2} - w_O}{w_O}$$

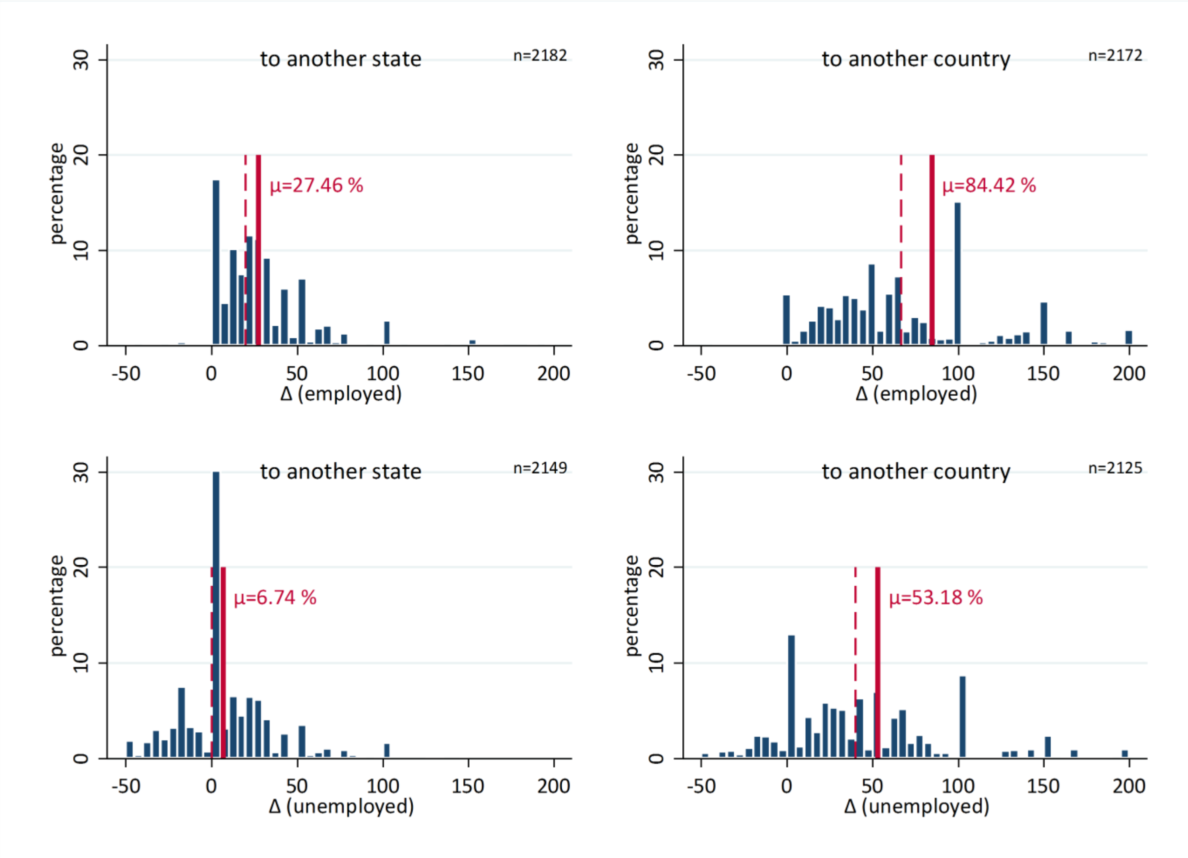
The subsequent analyses are based on a trimmed sample, where the lowest and the highest 0.5 % of responses have been excluded. Consistency checks and a validation of participants' response

101 Translated versions of those items involved in the construction of the four mobility premiums are listed in the appendix (Figure A6.1).

behaviour indicated that responses at these extreme ends are mostly related to a misunderstanding of reference values (monthly versus yearly benchmark). Within the econometric analysis (Chapter 6.5), I will also apply quantile regression in order to account for outliers in the data that remain within these two cutoff points.

A first glance at the mobility premiums' distributions in Figure 6.4 reveals already some noteworthy facts: the average expected mobility premium $\mu(\Delta_{A1})$ for an interstate move whilst having an alternative employment option at the origin amounts to 27.46 %. In case of cross-border mobility, the corresponding average expected premium $\mu(\Delta_{A2})$ is 84.42 %.

Figure 6.4: Mobility premiums, by destination and employment status



Note: The solid red line depicts the average mobility premium (μ); the dashed line corresponds to the median. Illustrated mobility premiums correspond to the four scenarios described in Chapter 6.3.2. The lower left panel, for instance, shows the histogram for Δ_{U1} being the expected mobility premium for moving to another state when unemployed. Each histogram bar covers an interval of five percentage points. For the sake of readability, the depicted premiums are confined to the interval [-50,200].

For the unemployment scenario, where $\pi_{UO,i}$ implicitly equals one, we observe the expected downward shift of the mobility premium in both migration scenarios. Most interestingly, the average internal mobility premium to avoid unemployment is still positive, i.e., $\mu(\Delta_{U1}) = 0.0674$. In contrast to the scenario assuming continued employment at the origin (upper left panel), half of the respondents were willing to accept a lower income level for the sake of finding employment elsewhere. The average cross-border mobility premium in the unemployment scenario drops by more than one third to $\mu(\Delta_{U2}) = 0.5318$. However, half of all respondents still featured an expected premium of more than 40 %.

From an economists' perspective, ignoring all personality parameters, a positive expected mobility premium in the unemployment scenario with $\pi_{UO,i} = 1$, $\pi_{EO,i} = 0$, and $\pi_{ED,i} = 1$ (as stated explicitly in the scenario) was largely related to monetary costs of moving, since the individual mobility premium would be given as

$$\varDelta_{U1,i} = \left[\left(\frac{p_{D1}}{p_O}\right)\left(\frac{a_O}{a_{D1}}\right)^{\frac{1-\alpha}{\alpha}}\eta_O + \frac{\Gamma_D + f(d_1)}{w_O}\right] - 1.$$

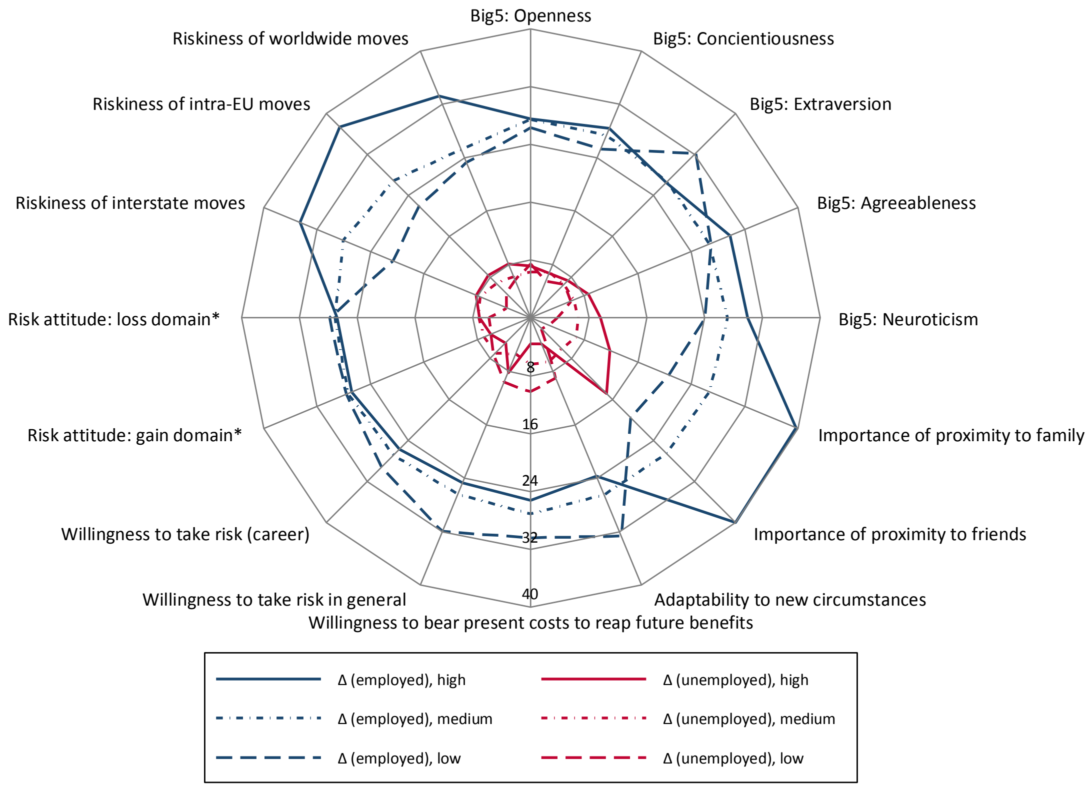
In case of a newly graduated individual without previous employment, implying non-eligibility to unemployment benefits ($\eta_O = 0$), relative costs of moving $(\Gamma_D + f(d_1))w_O^{-1}$ would induce in all likelihood $\varDelta_{U1,i} > 0$. Following this thought, one could derive that average expected costs of moving in relation to the reference income level were 106.74 % in the sample.[102]

Taking a broader perspective, and reintegrating the personality parameters in this scenario, the corresponding mobility premium is then

$$\varDelta_{U1,i} = \left[\left(\frac{p_{D1}}{p_O}\right)\left(\frac{a_O}{\gamma_{i1}(d_1)a_{D1}}\right)^{\frac{1-\alpha}{\alpha}}\eta_O + \frac{\Gamma_D + (1+\tau_i)f(d_1)}{w_O}\right] - 1.$$

Psychic costs of moving, entering via τ_i would now further increase the likelihood of observing a positive mobility premium.

Figure 6.5: Mobility premiums for internal migration scenarios, conditional on personality groupings (in %)



Note: * The solid line represents risk-loving individuals; the line with dashes and dots stands for risk-neutral and the dashed-line for risk-averse individuals. In all other cases, the three depicted groups refer to a classification based on standardised scores, such that 'medium' refers to those scoring within one standard deviation around the mean and 'high' ('low') comprises those more than one standard deviation above (below) the mean. The sample size varies across dimensions between 2120 and 2181.

[102] A similar reasoning applies if the relevant reference income would not be a labour market income but parental or social assistance.

This claim is supported by the descriptive findings depicted in Figure 6.5, where the unemployment scenario is illustrated in red. The closer to the graph's centre the smaller the group-specific average mobility premium, and vice versa. Participants who expressed a most pronounced preference of proximity to reference persons or who rated themselves as having a low adaptability to new circumstances also expect the highest mobility premium. If a person perceived an interstate move to be an especially risky endeavour, she would also exhibit a higher mobility premium. The tendency for more risk-averse persons to expect a higher mobility premium becomes more distinct for the scenarios assuming alternative employment at the origin (blue lines). Individuals scoring highest in the Big-Five trait neuroticism expect on average a mobility premium of 30.2 % in the employment scenario. Those on the opposite side of the scale exhibit an average mobility premium of 23.9 %.

Turning to the cross-border scenarios (Figure A6.2 in the appendix), group-specific mobility premiums are consistently larger in both labour market scenarios. In case of the trait neuroticism, the average expected cross-border mobility premium in an unemployment scenario of those scoring highest amounts to 56.1 %. Least neurotic individuals still require on average a premium 47.9 %, which is twice the size of the corresponding premium in the internal migration scenario.

In all likelihood, individuals will not perfectly adhere to some a priori formulated guess when they actually consider a move for employment reasons. Their initial expectations will nonetheless be of some relevance in the decision-making process. If someone was socially extremely well connected at the current place of residence, for instance had a high level of local social capital (David et al., 2010), leaving this place would be associated with substantial costs. Such a person might require an ex ante premium of one hundred or more percent, just to consider the mere possibility of moving and actually sending out an application. Though such a person might eventually deviate from this initial expectation during salary negotiations, e.g., ask for an implicit premium of 50 %, this person would still require a distinctly higher compensation than other, less rooted individuals.

Therefore, the illustrated average positive mobility premium in an unemployment scenario is a plausible factor explaining why individuals may choose to stay in an economically disadvantaged region even when unemployed: wage offers at alternative locations might be perceived as insufficient to compensate for mobility-related discomfort. Heterogeneous personalities or individual preferences and adjustment capabilities, in turn, are now likely candidates for understanding the distribution of mobility premiums under various circumstances.

6.5 Econometric analysis

To which extent do personality characteristics and preferences bear substantial explanatory power regarding expected mobility premiums of prospective academics? After a brief discussion of the applied estimation methods and model specifications in Chapter 6.5.1, this chapter provides a general perspective in Chapter 6.5.2 by presenting results from a pooled premium sample. In Chapter 6.5.3, scenario specific estimations are discussed. The fourth paragraph performs additional sensitivity checks, especially addressing concerns regarding the reliability of decisions in a hypothetical context and gender-specific elasticities.

6.5.1 OLS and quantile regression specifications

Across chapters, the premiums' conditional mean $E[\Delta|X]$ is estimated based on the linear model

$$\Delta = X'\beta_{OLS} + \varepsilon,$$

where robust standard errors are implemented to account for a potential violation of the underlying assumption of i.i.d. errors. Estimated coefficients β_{OLS} show by how many percentage points the mobility premium Δ changes on average if the corresponding explanatory variable x increases by one unit.

To account for a potentially biasing impact of outliers, mobility premiums are also estimated applying quantile regression.[103] In contrast to OLS, not the conditional mean function is estimated, but the conditional quantile function

$$Q[\Delta|X, q] = X'\beta_q$$

assuming that $Prob\left[\Delta \leq X'\beta_q \middle| X\right] = q$. The respective quantile is indicated by q, such that holds $q \in]0,1[$ (cf. Greene, 2012, p. 207). Derived estimates, e.g., $\beta_{0.50}$ or $\beta_{0.75}$, inform about the elasticities of Δ with respect to an explanatory variable at the median, respectively at 75th percentile of Δ. Implemented standard errors are bootstrapped (500 replications), which yields two merits: first, it evades the necessity to define a functional form of the so-called sparsity function, required for the calculation of the variance-covariance matrix even when residuals fulfil the i.i.d. assumption. Moreover, bootstrapped standard errors are not only an adequate measure to address heteroskedastic errors in this application (Rogers, 1992), but this inference method offers the additional advantage of performing simultaneous quantile estimation. Deriving quantile-specific coefficients simultaneously, and applying the bootstrap, yields a complete variance-covariance matrix of the estimators. The latter allows testing for equality of $\beta_{0.50}$ and other quantile-specific coefficients across equations (Gould, 1997). Non-rejection of the Null lends then support to the hypothesis of a constant variance, respectively an uphold assumption of homoscedastic residuals. An asymptotical convergence of OLS coefficients and median regression coefficients would in addition point to a sufficiently symmetric distribution of $\Delta|X$. In this case, the simple conditional mean function was capable of portraying the underlying relationships.

The matrix X contains the set of explanatory variables. Aside from socio-demographic variables it also contains the individual traits and location-specific conditions from the theoretical model.[104] The set of socio-demographic variables comprises in addition to gender, age, and partnership status also English language proficiency. Better English language skills Λ_i are supposed to facilitate integration

[103] Based on consistency checks, only the lowest and highest 0.5 % (11 cases in each tail) were excluded. Thus, outliers may still have a certain impact on estimates.

[104] An overview and corresponding descriptive statistics can be found in Table A6.2 in the appendix.

into a new living environment abroad, to reduce transaction costs in daily life, and to increase individual adjustment capability ($\partial\gamma_i/\partial\Lambda > 0$).

The location-specific conditions refer to the district a participant explicitly stated to be his current place of residence. Aside from mostly economic variables, such as GDP per capita, a price level measure and the unemployment rate, they also comprise a measure of urbanisation (population density). Aspects of urban interconnectedness are also integrated, based on variables representing the time it takes to reach the three closest agglomeration centres by either car or train. Amenity aspects are directly represented by a measure of access to recreational space and the provision of public goods, gauged by the relative number of communal employees.

Personality-related variables, such as willingness to take risks (in the career domain), patience and the Big-Five personality traits enter the model in categorical form. The same holds for the adaptability measure and the social preference variables. For each of these, a standardisation of the original scale variable yielded three distinct groups: the reference group comprising the average-type individuals ($\mu - \sigma \leq$ score $\leq \mu + \sigma$), as well as a group distinctly below and one distinctly above the mean μ, respectively the reference group. This procedure allows detecting some basic non-linear relationships across groupings. In most specifications, previous mobility experiences are controlled for as well. This includes earlier stays abroad and residential mobility during adolescence, as well as the most recent mobility experience, namely educational mobility.[105]

In addition, specifications incorporate the logarithm of the expected post-graduation income levels. This accounts for cases where individuals might just ask for a reimbursement of fixed monetary moving costs, which are not depending on distance. Comparable amounts, however, might correspond to largely varying mobility premiums, depending on the position in the distribution of expected incomes.

Another categorical variable is only relevant in the pooled analysis of mobility premiums. There, this component accounts for the different scenarios in which the mobility premiums have been derived.

6.5.2 Results from pooled specifications

Table 6.1 provides some preliminary guidance concerning the fundamental factors involved in the formation of mobility premiums by pooling observations from all four scenarios. The sample is restricted to those 1851 individuals with four non-missing premiums, yielding 7404 observations in total. Reported results are from the preferred specification, based on the full set of individual traits and location-specific conditions. The outcomes therefore correspond to the compensating differential models with heterogeneous preferences and personality. The first two columns' results are obtained by OLS, the next six columns display outcomes from the simultaneous quantile

[105] Educational mobility shall refer in this context to geographic mobility for educational purposes, i.e., attending a university. It is measured as excess distance, i.e., the difference of the distance between an individual's origin and the actually chosen study location and the distance between this origin and the closest university offering an economics programme.

regression ($q = 0.25, 0.50, 0.75$) with identical model specification. The last two columns display the results from a test for equality of coefficients across quantiles, e.g., $\beta_{0.25} = \beta_{0.50}$ and $\beta_{0.50} = \beta_{0.75}$. Model comparisons for OLS and quantile regressions are documented in Table A6.3 and Table A6.4 (in the appendix).[106]

Table 6.1: Results from pooled OLS and pooled quantile regression estimation

dependent variable	Δ (pooeld)		Δ (pooled)							
estimation method	OLS		QREG ($q = 0.25$)		QREG ($q = 0.50$)		QREG ($q = 0.75$)		Test of quantile coefficient equality	
	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	F	prob > F
gender (female=1)	-1.4270	(1.3706)	-0.8223	(0.8648)	-1.2135	(0.8926)	-1.5743	(1.4316)	0.19	0.8302
age	0.0132	(0.3135)	0.4592***	(0.1635)	0.1849	(0.1950)	-0.1495	(0.2708)	2.79	**0.0614**
partnership (yes=1)	4.5258***	(1.2187)	3.1488***	(0.7515)	3.9627***	(0.8387)	2.5378**	(1.2452)	1.22	0.2955
language skills (English)										
high	-5.4846**	(2.1700)	-1.7027	(1.2856)	-1.5020	(1.5810)	-2.3210	(2.0159)	0.09	0.9094
medium	-3.8161*	(2.0635)	-0.7153	(1.2197)	-1.0570	(1.3826)	-3.2240	(1.9776)	0.86	0.4250
risk attitude (career domain, ϕ_R)										
score $< \mu - \sigma$	3.2169**	(1.4854)	0.7002	(0.9210)	0.1983	(1.0705)	2.5212*	(1.5266)	1.72	0.1787
score $> \mu + \sigma$	1.9471	(2.0277)	-1.6094	(1.2062)	-0.0655	(1.4156)	2.3730	(1.9298)	2.19	0.1117
patience (ϕ_P)										
score $< \mu - \sigma$	5.5332***	(1.8439)	0.6229	(1.0105)	1.4625	(1.2219)	5.0169***	(1.7997)	3.20	**0.0406**
score $> \mu + \sigma$	-2.9838*	(1.6646)	-1.7237	(1.5269)	-0.7533	(1.2953)	-1.0334	(1.6585)	0.29	0.7480
extraversion (ψ_E)										
score $< \mu - \sigma$	-0.5623	(2.1348)	-2.2053*	(1.1677)	-1.9608	(1.4537)	-2.7433	(2.2622)	0.10	0.9072
score $> \mu + \sigma$	1.7294	(1.5828)	-1.4069	(1.0964)	-0.3685	(1.1690)	3.5314**	(1.5941)	4.90	**0.0075**
neuroticism (ψ_N)										
score $< \mu - \sigma$	-0.2922	(2.1250)	-2.0661*	(1.2178)	-2.7612**	(1.3452)	-4.4720**	(1.8903)	0.86	0.4248
score $> \mu + \sigma$	-0.5316	(1.6377)	1.1151	(0.9828)	-0.0781	(1.1009)	-0.6966	(1.9244)	0.72	0.4863
openness (ψ_O)										
score $< \mu - \sigma$	-2.2346	(1.6215)	-2.5920***	(0.9995)	-3.2312***	(1.1116)	-0.8117	(1.5281)	1.71	0.1818
score $> \mu + \sigma$	-0.4738	(1.6307)	-1.8978**	(0.9645)	-2.2190**	(1.0912)	-0.2057	(1.6147)	1.04	0.3520
conscientiousness (ψ_C)										
score $< \mu - \sigma$	-0.1602	(2.0614)	-1.5920	(1.2849)	-0.5805	(1.4783)	-0.4402	(2.0719)	0.33	0.7209
score $> \mu + \sigma$	-2.0733	(1.5892)	-1.6358	(1.1450)	0.1471	(1.2310)	0.6243	(1.7337)	1.26	0.2826
agreeableness (ψ_A)										
score $< \mu - \sigma$	0.4499	(1.6026)	-0.4319	(0.9551)	-1.3759	(1.0930)	-0.5001	(1.6305)	0.55	0.5786
score $> \mu + \sigma$	1.6450	(1.5898)	3.0968***	(1.1911)	2.4534**	(1.1239)	3.3136**	(1.6623)	0.33	0.7187
adaptability (ϕ_A)										
score $< \mu - \sigma$	6.4159***	(1.6698)	2.6821***	(1.0250)	3.1993***	(1.1196)	6.9878***	(2.2771)	2.14	0.1179
score $> \mu + \sigma$	-0.8650	(1.8667)	0.0555	(1.2673)	-0.6003	(1.2678)	-1.2421	(1.6625)	0.28	0.7568
importance of prox. (family, ϕ_S)										
score $< \mu - \sigma$	-2.9647*	(1.6278)	-3.0716***	(1.0334)	-4.2628***	(1.1381)	-3.4604**	(1.7207)	0.67	0.5103
score $> \mu + \sigma$	9.6209***	(2.1239)	3.6166**	(1.6598)	8.0606***	(1.7380)	10.4156***	(2.9412)	4.66	**0.0095**
importance of prox. (friends, ϕ_S)										
score $< \mu - \sigma$	-6.7878***	(1.6812)	-2.4733**	(1.1131)	-2.4134*	(1.2496)	-4.3304**	(1.7060)	0.80	0.4477
score $> \mu + \sigma$	10.4159***	(2.3144)	5.4241***	(1.5191)	7.8578***	(1.7804)	13.5379***	(3.3106)	3.47	**0.0312**
previous mobility experiences (χ)										
residential move (yes=1)	0.7753	(1.4290)	-0.8163	(0.9414)	1.1209	(1.1321)	1.7354	(1.5455)	1.84	0.1592
exchange participation (yes=1)	-3.8862***	(1.2788)	-1.0511	(0.8688)	-1.7724*	(0.9437)	-2.5715*	(1.3322)	0.72	0.4880
stay abroad (yes=1)	-10.7625***	(1.3930)	-6.8525***	(1.0687)	-6.2750***	(0.9967)	-7.4641***	(1.4534)	0.55	0.5763
educational mobility (km)	-0.0370***	(0.0060)	-0.0231***	(0.0037)	-0.0272***	(0.0045)	-0.0335***	(0.0052)	2.13	0.1194
local conditions at origin (a_O)										
GDP (per capita)	-0.8941***	(0.2075)	-0.4509***	(0.1247)	-0.3860***	(0.1310)	-0.5333**	(0.2232)	0.49	0.6111
building land prices	0.0915***	(0.0311)	0.0341	(0.0237)	0.0379*	(0.0205)	0.0513*	(0.0265)	0.19	0.8311
accessibility (train)	-0.1950***	(0.0525)	-0.0190	(0.0323)	-0.0863**	(0.0403)	-0.0942	(0.0580)	1.74	0.1759
accessibility (car)	0.0547	(0.1028)	-0.0348	(0.0637)	0.0090	(0.0716)	0.0178	(0.0968)	0.22	0.7996
pop. density	-0.0018	(0.0023)	-0.0005	(0.0013)	-0.0001	(0.0014)	-0.0015	(0.0020)	0.40	0.6692
recreational area (per capita)	0.0600**	(0.0274)	-0.0023	(0.0187)	0.0200	(0.0168)	0.0047	(0.0242)	0.94	0.3902
public services	0.0184	(0.0467)	0.0295	(0.0290)	0.0086	(0.0276)	0.0249	(0.0428)	0.34	0.7146
unemployment rate (π_{UO})	-1.7269***	(0.6611)	-0.7109*	(0.3846)	-0.9459**	(0.4045)	-0.7000	(0.6272)	0.29	0.7481
premium type controls	✓		✓		✓		✓			
relative income control (w_0)	✓		✓		✓		✓			
constant	✓		✓		✓		✓			
observations	7404		7404		7404		7404			
df (model)	41		41		41		41			
F-statistic	65.04									
prob > F	0.0000									
R-squared / pseudo R-squared	0.2800		0.1538		0.1820		0.2223			
adjusted R-squared	0.2760									

*** p<0.01, ** p<0.05, * p<0.1

Note: Heteroscedasticity robust standard errors are implemented in case of the OLS model. Standard errors in the simultaneous quantile regression are bootstrapped (500 replications). These standard errors are also used in the test for coefficient equality across the three quantiles. Depicted p-values in bold indicate significant differences of quantile coefficients at the conventional significance levels. The pseudo R-squared for the quantile regressions is calculated as 1-(minimum sum of deviations/absolute sum of deviations).

[106] These model comparisons inform about the sensitivity of results with respect to the inclusion of additional personality traits.

Typically, significant coefficient estimates in the OLS specification are closest to those from the upper quartile ($q = 0.75$) in the simultaneous quantile regression. This yields evidence in favour of outliers inflating mobility premium estimates in the OLS case. With exemption of the Big-Five estimates, the conditional mean provides some general guidance regarding factors that may increase or mitigate the expected mobility premium.

Across the three quantiles, two traits display significant explanatory power: least neurotic individuals request negative mobility premiums between -2.1 and -4.5 percentage points. Most agreeable individuals, in contrast ask for an additional premium of 2.5 to 3.3 percentage points. If these individuals expect episodes of labour mobility to be prompted by a future employer, they might expect a compensation for showing such distinct form of commitment to the requirements of the job. And indeed, there is evidence that agreeableness and job performance are positively correlated (Mount et al., 1998), respectively agreeable individuals evince also higher levels of job involvement (Liao and Lee, 2009), becoming potentially more likely to meet such a requirement.

Across specifications and estimation methods, individuals in a partnership expect a 2.5 to 4.5 percentage point higher mobility premium. In accordance with expectations, least patient individuals expect on average a mobility premium of 5.5 percentage points. Quantile regression results indicate that this trait is especially relevant for the upper quartile in the mobility premium distribution. The observed difference across coefficients is also significant (p=0.0406). OLS estimates point to a significant risk-related component in the mobility premium, around 3 percentage points, which is only reflected in quantile regression results for the 75th percentile.[107]

Adaptability to new circumstances, a measure also related to the concept of hedonic adaptation (Frederick and Loewenstein, 1999; Graham and Oswald, 2010) proves to be relevant across specifications and quantiles. Individuals rating themselves as least adaptable to new circumstances expect on average mobility premiums that are 6.4 percentage points above those of the reference group, consisting of respondents of medium adaptability. Quantile regression results support this finding while the coefficient is twice the size for the upper quartile compared to the median or the lower quartile.

Social preferences, including the importance of proximity to reference persons, feature across all specifications not only a substantial degree of significance but also size. In absolute terms, the coefficients for proximity to peers are most of the times more pronounced than for family. Each time the coefficients for both subgroups, comprising individuals either with below or above average preferences, show the expected sign in relation to the reference group. Social ties seem to play a huge role: if an individual has a distinctive affinity to familiar reference persons, the observed mobility premium is 21 percentage points higher.[108] This lends strong support in favour of the psychic

[107] Model comparisons in Table A6.3 and Table A6.4 show that this risk-related element of mobility premiums diminishes when social preferences are accounted for.

[108] For an individual scoring highest in importance of family and friends, the overall magnitude is the sum of 9.6 and 10.4 percentage points.

costs theory – if existing social ties are especially relevant, people expect to be compensated more copiously for the discomfort of moving and being apart from familiar reference persons. The coefficients' relative size is in line with findings of Dahl and Sorenson (2010), who documented technical workers' high valuation of proximity to their parents or former classmates.[109] This suggests that factors of high relevance in a real-world context can also be uncovered in an analysis of expected ex ante premiums.

Previous mobility experiences, supposed to strengthen adjustment capabilities in the model, are indeed associated with lower expected mobility premiums in the pooled specifications. Participants who spent some time abroad expected in the pooled approach on average a 10.8 percentage point smaller premium. Those who displayed higher levels of educational mobility, hence selected themselves into more remote study locations in the first place, require a smaller premium as well: those who chose a destination 100 kilometres beyond the closest alternative feature an ex ante mobility premium which is diminished by 3.7 percentage points. Across specifications, residential mobility during adolescence does not exhibit any explanatory power – the impact of mobility experiences in the distant past seem to fade out over time.

Turning to the potential relationship between location-specific conditions, such as amenities or unemployment likelihood, significant coefficients exhibit with one exception the expected sign. The lower the degree of accessibility of agglomeration centres, measured as longer travel time by train, the lower the expected mobility premium. For one, this points towards a fundamental value of being geographically well connected and having access to metropolitan markets or amenities. But then, in conjuncture with an insignificant coefficient for accessibility by car, this result suggests that cars are not the crucial means of transportation for this cohort. Similarly, individuals already residing in cities with better recreational opportunities, measured as recreational area per inhabitant, would want higher compensation for leaving such a favourable environment, offering a high recreational value. The provision of public services, accounted for as public employees in relation to population, constitutes an amenity which does not display a significant association in the pooled specifications.

Building land prices on the district level as proxy for housing prices (thus in the end rents as well) deliver the expected results, consistent with the literature on compensating differentials: these prices capitalise to a substantial degree local amenity levels. People from municipalities where building prices are one standard deviation higher expect on average an additional mobility premium of almost 7.5 percentage points.[110]

GDP per capita at the district level, the measure for general material well-being, is the mentioned outlier. One would have expected that, controlling for unemployment risk, individuals from relatively richer regions would request higher compensations. Albeit, there is a possible explanation for this result: if individuals from high income districts have a more wealthy background, their overall

[109] Doubling the distance to the former is related to an annual income compensation between $ 5263 and $ 12753.

[110] Calculated as $\beta_{OLS}^{p} \times std.dev = 0.0915 \times 82.01 = 7.5039$

financial position could be more favourable so they would possibly put less weight on potential income gains from migration.

In accordance with the sketched model, labour market conditions prove to be relevant as well. A higher unemployment rate is across all specifications indicative of significantly lower mobility premiums. A one percentage point higher unemployment rate lowers the expected mobility premium by 0.7 to 1.7 percentage points – perceived unemployment risk thus reduces indeed the value of staying.

6.5.3 Scenario-specific results

Within the examination of internal mobility premiums, both the one with job alternative (Δ_{A1}) and the other assuming unemployment (Δ_{U1}), the preferred model specifications are with one exemption the same as in the pooled analyses.[111]

Common to the pooled specification, previous mobility experiences and preferences regarding social proximity are the most relevant factors explaining internal mobility premiums (Table 6.2). In the domain of adjustment capabilities one can nevertheless observe some differences too, especially between the scenario assuming existing job alternative and the scenario assuming unemployment. Only in the first one, individuals with short-term cross-border mobility experience (exchange participation) reduce on average the expected mobility premium. In the unemployment scenario, this factor loses its predictive power. A longer stay abroad and higher levels of education mobility are associated with distinctly mitigated mobility premiums across both internal scenarios and estimation methods.

Least adaptable individuals expect on average internal premiums of around 3 percentage points, which is not diminished in the unemployment scenario. This trait proves to be relevant for individuals in the lower or upper quartiles as well (Table A6.7).

There are also some noteworthy differences between the two labour market scenarios. Family ties, for instance, seem to lose their relevance in an unemployment scenario. Desired proximity to friends, in contrast, still implies higher psychic costs, which have to be more heavily compensated to induce mobility. The network of friends might have a higher value, e.g., a peer network might provide information on job openings. At the same time, women expect in the unemployment scenario on average a slightly higher ex ante mobility premium than men. This is further evidence that women display a different place attachment then men, even when controlling for social factors.[112]

Exclusively focusing on internal migration scenarios, risk attitude is not significantly related to observed mobility premiums in either scenario. English language skills are irrelevant in these specifications as well. In accordance with the hypothesis that language facilitates integration into a

[111] The only modification is related to scenario-specific estimations, and hence scenario-dummies are no longer required.

[112] This result should not driven by issues of childcare, since all women in the sample are currently enrolled in tertiary education and in their early twenties.

new living environment, English language proficiency should not affect outcomes when it comes to German interstate migration.

Table 6.2: Internal mobility premiums (OLS and quantile regression)

dependent variable	Δ_{A1} (internal, given alternative job)				Δ_{U1} (internal, given unemployment)			
estimation method	OLS		QREG ($q = 0.50$)		OLS		QREG ($q = 0.50$)	
	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.
gender (female=1)	-0.7197	(1.3516)	-0.9017	(1.2214)	2.8991*	(1.4818)	1.7487	(1.2892)
age	-0.0424	(0.2950)	-0.0187	(0.2440)	0.8025**	(0.3497)	0.4372	(0.2670)
partnership (yes=1)	1.7965	(1.1705)	2.3455**	(1.0442)	1.7942	(1.3101)	1.2333	(1.2056)
language skills (English)								
high	0.2028	(1.9403)	-0.0976	(1.8628)	0.3641	(2.2884)	0.0329	(2.6217)
medium	-0.9351	(1.7837)	-0.4944	(1.6351)	-1.0436	(2.0699)	-0.9261	(2.4762)
risk attitude (career domain, ϕ_R)								
score $< \mu - \sigma$	1.0668	(1.4569)	0.7023	(1.3751)	-0.8305	(1.5940)	-1.0173	(1.4012)
score $> \mu + \sigma$	1.5480	(1.7940)	1.5708	(2.0496)	-0.3313	(2.0657)	-1.1009	(1.4471)
patience (ϕ_P)								
score $< \mu - \sigma$	3.5968**	(1.6727)	0.2906	(2.0386)	2.8933	(1.8766)	1.7316	(1.5801)
score $> \mu + \sigma$	-0.8534	(1.5963)	0.1157	(1.6530)	-2.8192	(1.8302)	-1.0277	(1.6726)
extraversion (ψ_E)								
score $< \mu - \sigma$	2.5990	(1.8788)	0.6761	(1.6822)	-2.6948	(2.2157)	-3.4274*	(1.7488)
score $> \mu + \sigma$	-0.1800	(1.4925)	-0.0070	(1.5925)	1.1296	(1.7892)	**0.1050**	(1.5865)
neuroticism (ψ_N)								
score $< \mu - \sigma$	-1.4558	(1.8312)	-2.3317	(1.9368)	-1.0017	(2.0034)	-0.5588	(1.4935)
score $> \mu + \sigma$	0.8838	(1.6923)	1.1700	(1.6059)	1.4164	(1.8689)	-0.5578	(1.6989)
openness (ψ_O)								
score $< \mu - \sigma$	-3.3878**	(1.4769)	-2.1224	(1.4575)	-1.3327	(1.7242)	-2.2063	(1.7063)
score $> \mu + \sigma$	-2.5564*	(1.5025)	-2.0828	(1.5313)	0.4247	(1.7016)	-0.9624	(1.3139)
conscientiousness (ψ_C)								
score $< \mu - \sigma$	-0.2856	(1.8096)	0.1793	(1.9662)	0.5959	(2.2331)	-0.4277	(1.9040)
score $> \mu + \sigma$	-0.2953	(1.5997)	0.6376	(1.7324)	-1.5744	(1.8060)	-1.0854	(1.6084)
agreeableness (ψ_A)								
score $< \mu - \sigma$	-0.1304	(1.5247)	-0.8473	(1.4629)	0.4803	(1.7744)	-0.3515	(1.5270)
score $> \mu + \sigma$	3.1860*	(1.6513)	3.6829**	(1.6189)	2.9933*	(1.6798)	0.8348	(1.5329)
adaptability (ϕ_A)								
score $< \mu - \sigma$	3.2690**	(1.5967)	**2.5528**	(1.6570)	3.2048*	(1.8258)	1.1499	(1.7967)
score $> \mu + \sigma$	1.1230	(1.7819)	0.2607	(2.0337)	0.7855	(1.8689)	0.7450	(1.6411)
importance of proximity (family, ϕ_S)								
score $< \mu - \sigma$	-2.0220	(1.5136)	-3.3319*	(1.7281)	-0.6128	(1.7450)	-1.4920	(1.2705)
score $> \mu + \sigma$	6.8777***	(2.1252)	6.4863***	(2.0921)	-0.0198	(2.3834)	2.0976	(2.8287)
importance of proximity (friends, ϕ_S)								
score $< \mu - \sigma$	-4.1752***	(1.6051)	-2.8224	(1.8835)	-2.6304	(1.8219)	0.5690	(1.4218)
score $> \mu + \sigma$	6.0000***	(2.1067)	5.2766**	(2.0472)	6.0702**	(2.4882)	6.4117**	(3.2032)
previous mobility experiences (χ)								
residential move (yes=1)	0.6710	(1.3230)	0.9114	(1.4143)	-0.0689	(1.5600)	-0.6078	(1.3071)
exchange participation (yes=1)	-2.6014**	(1.2690)	-0.9302	(1.2463)	-1.4469	(1.4204)	-0.7153	(1.3238)
stay abroad (yes=1)	-4.7414***	(1.5033)	-4.6585***	(1.4081)	-4.1557***	(1.6069)	-3.2052**	(1.4134)
educational mobility (km)	-0.0239***	(0.0058)	-0.0185***	(0.0062)	-0.0254***	(0.0060)	**-0.0112***	(0.0060)
local conditions at origin (a_O)								
GDP (per capita)	-0.4408**	(0.1916)	-0.2952*	(0.1682)	-0.4078**	(0.2025)	-0.0737	(0.2121)
building land prices	0.0868***	(0.0278)	0.0498**	(0.0235)	0.0237	(0.0314)	-0.0097	(0.0258)
accessibility (train)	-0.0881*	(0.0508)	**-0.0479**	(0.0437)	-0.0824	(0.0570)	-0.0279	(0.0569)
accessibility (car)	-0.0444	(0.0903)	-0.0800	(0.0833)	0.0524	(0.1056)	-0.0530	(0.1043)
pop. density	-0.0032*	(0.0018)	-0.0001	(0.0018)	-0.0022	(0.0021)	-0.0025	(0.0020)
recreational area (per capita)	0.0216	(0.0220)	0.0227	(0.0189)	-0.0181	(0.0275)	-0.0244	(0.0233)
public services	-0.0199	(0.0410)	-0.0332	(0.0328)	0.0630	(0.0473)	0.0297	(0.0450)
unemployment rate (π_{UO})	-0.4863	(0.5302)	-1.0188*	(0.5216)	-0.4212	(0.6319)	-0.0171	(0.6068)
relative income control (w_0)	✓		✓		✓		✓	
constant	✓		✓		✓		✓	
observations	1851		1851		1851		1851	
df (model)	38		38		38		38	
F-statistic	7.75				3.64			
prob > F	0.0000				0.0000			
R-squared / pseudo R-squared	0.1280		0.0827		0.0834		0.0136	
adjusted R-squared	0.1097				0.0642			

*** p<0.01, ** p<0.05, * p<0.1

Note: Depicted coefficients in bold indicate significant differences of quantile coefficients at the conventional significance levels. Heteroscedasticity robust standard errors have been applied in case of the OLS model. Standard errors in the simultaneous quantile regression are bootstrapped (500 replications). These s.e. are also used in the test for coefficient equality across the three quantiles.

On this disaggregated level, amenity levels at the origin become less reliable predictors, although the concept of building prices as overall proxy for amenities remains a significant factor in the employment scenario. This, in turn, implies that individuals facing unemployment lower their valuations of current amenity levels.

Cross-border mobility premiums are not only larger in absolute terms, but feature a higher elasticity with respect to personality and preference parameters too (Table 6.3): whenever a coefficient is significant in the cross-border specification, it is typically at least twice the size of the corresponding coefficient from the internal specifications.

Table 6.3: Cross-border mobility premiums (OLS and quantile regression)

dependent variable	Δ_{A2} (cross-border, given alternative job)				Δ_{U2} (cross-border, given unemployment)			
estimation method	OLS		QREG ($q = 0.50$)		OLS		QREG ($q = 0.50$)	
	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.
gender (female=1)	-6.6906*	(3.7114)	-8.0174**	(3.2287)	-1.1969	(3.4233)	-0.9467	(3.5209)
age	-0.9193	(0.8142)	-0.0054	(0.5998)	0.2120	(0.7946)	0.2948	(0.7595)
partnership (yes=1)	6.5887**	(3.3320)	3.5618	(2.7755)	7.9239***	(3.0381)	9.2024***	(3.1057)
language skills (English)								
high	-14.2812**	(6.0308)	-7.5312	(4.8099)	-8.2240	(5.4485)	-4.9049	(4.5984)
medium	-7.8434	(5.8127)	-2.6918	(4.4189)	-5.4423	(5.1402)	-1.5507	(4.2560)
risk attitude (career domain, ϕ_R)								
score $< \mu - \sigma$	8.0559**	(4.0247)	2.4987	(3.6288)	4.5753	(3.6874)	2.4989	(3.6904)
score $> \mu + \sigma$	6.4476	(6.0069)	-1.4637	(4.1716)	0.1243	(4.6659)	-5.9945	(4.7704)
patience (ϕ_P)								
score $< \mu - \sigma$	8.1635	(5.0376)	**6.1090**	(4.5438)	7.4790	(4.7347)	-0.1297	(3.8332)
score $> \mu + \sigma$	-3.4149	(4.6005)	2.9340	(3.8066)	-4.8476	(4.0071)	-4.2727	(4.3310)
extraversion (ψ_E)								
score $< \mu - \sigma$	4.6261	(6.1318)	0.0552	(4.4084)	-6.7797	(5.1057)	-13.8425**	(5.4124)
score $> \mu + \sigma$	1.7766	(4.4112)	-1.1286	(3.8128)	4.1911	(3.8364)	-0.2514	(3.7655)
neuroticism (ψ_N)								
score $< \mu - \sigma$	2.5899	(6.3460)	-6.9390	(4.9512)	-1.3012	(4.8876)	-3.2947	(4.4597)
score $> \mu + \sigma$	-4.2229	(4.2936)	-0.5503	(3.4719)	-0.2036	(4.1454)	-0.7242	(4.4543)
openness (ψ_O)								
score $< \mu - \sigma$	-4.6182	(4.3390)	-4.9739	(3.6924)	0.4002	(4.1392)	-2.9984	(4.2988)
score $> \mu + \sigma$	-0.7239	(4.5052)	-1.1056	(4.2079)	0.9603	(4.0291)	-4.1780	(3.4982)
conscientiousness (ψ_C)								
score $< \mu - \sigma$	-2.1957	(5.6295)	-3.2834	(5.4462)	1.2447	(5.2145)	1.3620	(4.6801)
score $> \mu + \sigma$	-3.0004	(4.3060)	2.8240	(3.7541)	-3.4233	(3.8873)	0.0633	(4.3371)
agreeableness (ψ_A)								
score $< \mu - \sigma$	0.0486	(4.3776)	0.1601	(4.0343)	1.4011	(3.9828)	-2.0572	(3.6609)
score $> \mu + \sigma$	1.4983	(4.4005)	5.2134	(4.0921)	-1.0977	(3.8906)	1.0174	(3.7160)
adaptability (ϕ_A)								
score $< \mu - \sigma$	8.8515**	(4.4889)	6.6691	(4.5743)	10.3383**	(4.1936)	5.9646	(4.2360)
score $> \mu + \sigma$	-3.0120	(5.6145)	-5.1846	(4.1521)	-2.3565	(4.0201)	2.4811	(4.4360)
importance of proximity (family, ϕ_S)								
score $< \mu - \sigma$	-5.5772	(4.6928)	-9.1449**	(3.6249)	-3.6467	(3.8005)	-6.1431*	(3.4789)
score $> \mu + \sigma$	19.4975***	(5.5309)	23.0422***	(5.6191)	12.1282**	(5.4026)	7.0679	(6.5728)
importance of proximity (friends, ϕ_S)								
score $< \mu - \sigma$	-11.6357**	(4.7672)	**-7.4532****	(3.7608)	-8.7098**	(3.9763)	-3.4491	(4.2238)
score $> \mu + \sigma$	14.7322**	(6.0359)	10.6885*	(6.2068)	14.8613**	(5.9456)	14.6681**	(6.7079)
previous mobility experiences (χ)								
residential move (yes=1)	1.0977	(3.9437)	-0.0260	(3.5325)	1.4013	(3.5242)	1.1609	(3.4606)
exchange participation (yes=1)	-7.7866**	(3.4505)	**-3.7527**	(2.7751)	-3.7100	(3.1709)	-3.5601	(3.3276)
stay abroad (yes=1)	-16.9764***	(3.8522)	-12.6476***	(3.1778)	-17.1766***	(3.2677)	-11.4687***	(3.6994)
educational mobility (km)	-0.0535***	(0.0169)	-0.0366**	(0.0143)	-0.0454***	(0.0140)	**-0.0271****	(0.0132)
local conditions at origin (a_O)								
GDP (per capita)	-1.4459**	(0.5720)	-0.7290	(0.4876)	-1.2819**	(0.5165)	-0.4098	(0.4622)
building land prices	0.1760**	(0.0833)	0.1457**	(0.0678)	0.0795	(0.0784)	0.0441	(0.0679)
accessibility (train)	-0.2835**	(0.1406)	-0.2364*	(0.1219)	-0.3259**	(0.1314)	-0.2013	(0.1227)
accessibility (car)	0.1183	(0.2784)	0.2665	(0.2065)	0.0923	(0.2594)	0.2109	(0.2335)
pop. density	-0.0020	(0.0063)	-0.0016	(0.0049)	0.0001	(0.0058)	-0.0010	(0.0047)
recreational area (per capita)	0.1261*	(0.0711)	0.0793	(0.0551)	0.1105	(0.0717)	0.0322	(0.0462)
public services	-0.0331	(0.1287)	-0.0900	(0.1105)	0.0637	(0.1141)	-0.0147	(0.0957)
unemployment rate (π_{UO})	-2.9644*	(1.7863)	-0.6903	(1.3117)	-3.0359*	(1.7150)	-1.0407	(1.2903)
relative income control (w_0)	✓		✓		✓		✓	
constant	✓		✓		✓		✓	
observations	1851		1851		1851		1851	
df (model)	38		38		38		38	
F-statistic	7.17				6.41			
prob > F	0.0000				0.0000			
R-squared / pseudo R-squared	0.1093		0.0761		0.1080		0.0572	
adjusted R-squared	0.0906				0.0893			

*** p<0.01, ** p<0.05, * p<0.1

Note: Depicted coefficients in bold indicate significant differences of quantile coefficients at the conventional significance levels. Heteroscedasticity robust standard errors have been applied in case of the OLS model. Standard errors in the simultaneous quantile regression are bootstrapped (500 replications). These standard errors are also used in the test for coefficient equality across the three quantiles.

Important factors are once again previous mobility experiences and adaptability, both fostering adjustment capabilities. Beyond that, English language proficiency is also significantly related to cross-border mobility premiums in the alternative job scenario: highest levels of language proficiency (native-speakers and those speaking fluently in all situations), are paralleled by reduced mobility premiums by more than 14 percentage points. Contrasting these results with the OLS model comparison in Table A6.6 clarifies why English skills display no significance in the cross-border unemployment scenario: without previous mobility experiences, they are highly significant too. This suggests that language proficiency and previous mobility are interrelated and act jointly as facilitators to future cross-border mobility.[113] These results hold also for the lower quartile (Table A6.7) and portend to English as lingua franca, which can serve as means to reduce barriers to cross-border mobility by lowering perceived transaction costs.

Social preferences prove to be robust predictors of mobility premiums, accordingly to the modelling approach of psychic costs. People who value their existing social ties highly strive to maintain them. Those who are in a relationship feature in contrast to the internal scenarios now a markedly positive premium. Whilst internal work migration over, by all likelihood, a shorter distance would in principle allow a weekend relationship, this would probably change when a cross-border move is considered. Perceived psychic costs in such a cross-border scenario were substantial. Hence, to tip the scale in favour of inducing geographically mobile behaviour requires a larger weight, corresponding to a higher mobility premium in both scenarios.

Moving to another country might be considered as a relatively radical change, especially in the case of try-your-luck migration with a job alternative back home. This can be seen in the employment scenario, where the least risk prone individuals expect on average a cross-border mobility premium of 8.1 percentage points, and those in the upper quartile a 12 percentage point premium (Table A6.7). Local conditions display mostly the familiar patterns, yet there is one distinction: those living in less accessible regions exhibit now across scenarios on average a significantly negative premium.

In contrast to the internal try-your-luck scenario, women display on average a markedly negative cross-border mobility premium in the try-your-luck scenario. This finding remains valid across all three quartiles. Controlling for social preferences, personality and individual traits, these outcomes still point to gender-specific decision-making processes in the context of labour mobility. The resulting price of mobility may thus vary distinctly between women and men - some aspects in the underlying decision-making process may be valued differently. This is further investigated in a subsequent sensitivity check.

6.5.4 Sensitivity checks

A first sensitivity check is applied to cope with the hypothetical nature of the underlying scenarios, where respondents have been asked to state the expected monthly net income that would make them willing to move to another location. Undoubtedly, an intention to migrate does not always coincide with a subsequent migratory decision as many intervening factors could become relevant.

[113] Separate regressions (not reported) show that this is mostly related to 'stay abroad' and 'exchange participation'

Lu (1999), for instance, presented some evidence that intentions and actual behaviour of households without children are more congruent than for households with children. Given the sample at hand, consisting of students in their early twenties before the typical age of family formation, any realisation of a plan should not be limited by parenting obligations. Therefore, mobility intentions should be valid precursors of mobility outcomes.

In this regard, the theory of planned behaviour (summarised by Ajzen, 1991) provides some guidance under which circumstances a hypothetical statement can be a reliable precursor of actual behaviour: assuming a person has *actual behavioural control* over an outcome, stronger *intentions* together with more pronounced levels of *perceived behavioural control* would result in a higher likelihood that someone actually performs a certain behaviour.[114] Conveying this concept to the migration scenarios at hand, actual volitional control implies merely that someone was physically able to migrate and had the (financial) resources to do so.

Conner and Armitage (1998) suggested in their review of the theory of planned behaviour the inclusion of additional components, such as past behaviour or habit, to understand behavioural outcomes. Past mobility experiences, however, have already been included in the previously discussed specifications since they function as facilitators of future mobility by strengthening individuals' adjustment capability.

Based on this theoretical ground, two new components are introduced: the first is a measure of perceived behavioural control (θ_R), i.e., the perceived probability of succeeding at a given migratory path.[115] This perceived success probability is proxied by individuals' assessment regarding the riskiness of a specific move, e.g., to another state or another country. The second new component (θ_M) captures additional migration intentions, which are integrated as expected likelihood of moving to another state (or country in Europe) in the first five years after graduation.

Following the theory of planned behaviour, accounting for perceived behavioural control and migration-related intentions should be a valid strategy to uncover factors that are not only significant predictors in a hypothetical scenario but also likely to affect the mobility premium in case of a real-life move. Table 6.4 reports the results for the preferred specification for the four scenarios.

The main findings remain robust with respect to the preferred full specifications from the scenario-specific regressions (Table 6.2 and Table 6.3). Nevertheless, some differences emerge as well. Accounting for an extended parameter set, a notable increase of the adjusted R-squared value across all scenarios indicates that explanatory power increases substantially. The additional variables, representing behavioural control over the success of the migration outcome (riskiness of move, θ_R)

[114] Within the theory of planned behaviour, intentions are shaped by individual attitudes towards a behaviour and subjective norms, based on relevant persons' judgement whether a behaviour is desirable or not. Intentions can also be partially affected by perceived behavioural control.

[115] In this context, the findings of Lu (1999) can be rationalised: children might limit the perceived behavioural control since a parent might integrate the a priori unknown migration-related hardship to her children.

and the basic migration intentions (likelihood of a move, θ_M) manage to boost the estimations' precision.

Table 6.4: Sensitivity check (A) – the theory of planned behaviour

dependent variable	Δ_{A1} (internal, given alternative job)		Δ_{U1} (internal, given unemployment)		Δ_{A2} (Europe, given alternative job)		Δ_{U2} (Europe, given unemployment)	
estimation method	OLS		OLS		OLS		OLS	
	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.
gender (female=1)	0.3287	(1.3192)	3.7031**	(1.4785)	-3.5915	(3.6478)	1.3906	(3.3904)
age	-0.0785	(0.2937)	0.7579**	(0.3542)	-1.4356*	(0.8088)	-0.2010	(0.7928)
partnership (yes=1)	1.1892	(1.1452)	1.5155	(1.3031)	4.1322	(3.2611)	6.0888**	(3.0092)
language skills (English)								
high	0.4485	(1.9188)	0.6705	(2.2713)	-9.6444	(6.0143)	-4.4365	(5.4476)
medium	-0.5597	(1.7682)	-0.6893	(2.0502)	-5.3815	(5.8175)	-3.1786	(5.1497)
risk attitude (career domain, ϕ_R)								
score $< \mu - \sigma$	0.2254	(1.4214)	-1.4452	(1.5817)	5.4697	(3.9726)	2.3775	(3.6681)
score $> \mu + \sigma$	1.5500	(1.7467)	-0.4954	(2.0339)	7.8506	(5.9399)	0.9763	(4.5184)
patience (ϕ_P)								
score $< \mu - \sigma$	3.0206*	(1.6468)	2.4493	(1.8687)	6.2271	(4.8314)	5.8944	(4.5942)
score $> \mu + \sigma$	0.3386	(1.5548)	-2.1207	(1.8379)	-1.2457	(4.3488)	-3.5588	(3.8927)
extraversion (ψ_E)								
score $< \mu - \sigma$	1.4483	(1.8455)	-3.2579	(2.1900)	4.2164	(6.0549)	-7.0070	(5.0767)
score $> \mu + \sigma$	0.0232	(1.4710)	1.2074	(1.7818)	4.0492	(4.2876)	6.1074	(3.7380)
neuroticism (ψ_N)								
score $< \mu - \sigma$	-1.4020	(1.7533)	-0.8003	(1.9891)	2.5059	(6.0797)	-1.1782	(4.7147)
score $> \mu + \sigma$	0.9539	(1.6653)	1.4162	(1.8559)	-6.4830	(4.1554)	-2.3119	(4.0188)
openness (ψ_O)								
score $< \mu - \sigma$	-3.6350**	(1.4636)	-1.9006	(1.7068)	-6.3428	(4.3231)	-1.3168	(4.1051)
score $> \mu + \sigma$	-2.0719	(1.4618)	0.6612	(1.6883)	0.6194	(4.3854)	1.8001	(3.9655)
conscientiousness (ψ_C)								
score $< \mu - \sigma$	-0.1243	(1.7634)	1.0300	(2.2169)	-2.7054	(5.4537)	0.5621	(5.1433)
score $> \mu + \sigma$	-0.5895	(1.5481)	-1.8254	(1.7989)	-3.7551	(4.1810)	-4.9366	(3.7416)
agreeableness (ψ_A)								
score $< \mu - \sigma$	0.4704	(1.4878)	0.9381	(1.7497)	0.1299	(4.2642)	1.4642	(3.8778)
score $> \mu + \sigma$	2.3802	(1.6349)	2.4727	(1.6736)	2.0843	(4.2936)	-0.9279	(3.8300)
adaptability (ϕ_A)								
score $< \mu - \sigma$	2.4716	(1.5899)	3.2022*	(1.8185)	7.1185	(4.4212)	9.1852**	(4.1474)
score $> \mu + \sigma$	2.0307	(1.7959)	0.9386	(1.8961)	-0.6299	(5.7053)	-1.4982	(4.0459)
importance of proximity (family, ϕ_S)								
score $< \mu - \sigma$	-1.0271	(1.4950)	-0.4701	(1.7302)	-1.9117	(4.7013)	-1.1761	(3.7987)
score $> \mu + \sigma$	6.0926***	(2.0843)	-0.5438	(2.3679)	15.4355***	(5.3842)	8.2114	(5.2943)
importance of proximity (friends, ϕ_S)								
score $< \mu - \sigma$	-4.0571***	(1.5677)	-2.5203	(1.8164)	-9.2514**	(4.6314)	-6.9912*	(3.9554)
score $> \mu + \sigma$	4.4351**	(2.0764)	5.0743**	(2.4345)	9.5718	(5.8711)	10.4055*	(5.7974)
riskiness of move (θ_R)								
score $< \mu - \sigma$	-3.6693***	(1.3859)	-1.0147	(1.5137)	-14.4132***	(4.3262)	-7.3503*	(3.9429)
score $> \mu + \sigma$	1.0155	(1.7403)	-1.6232	(1.9262)	5.0986	(6.2010)	8.4289	(6.3750)
likelihood of move (θ_M)								
score $< \mu - \sigma$	13.5827***	(1.7715)	9.5430***	(1.9510)	32.2415***	(5.7392)	27.4992***	(5.2949)
score $> \mu + \sigma$	-2.5582*	(1.3849)	-1.4206	(1.5782)	-19.3846***	(3.3651)	-12.6224***	(3.0043)
previous mobility experiences (χ)								
residential move (yes=1)	0.8984	(1.3139)	0.0093	(1.5480)	2.7119	(3.9068)	2.0721	(3.5225)
exchange participation (yes=1)	-1.7648	(1.2523)	-0.8655	(1.4149)	-6.0357*	(3.4124)	-2.1439	(3.1420)
stay abroad (yes=1)	-4.1823***	(1.4606)	-4.0639**	(1.6231)	-11.0323***	(3.7134)	-12.9210***	(3.1856)
educational mobility (km)	-0.0136**	(0.0058)	-0.0195***	(0.0059)	-0.0418**	(0.0165)	-0.0372***	(0.0138)
local conditions at origin (a_O)								
GDP (per capita)	-0.3400*	(0.1828)	-0.3561*	(0.1956)	-1.3585**	(0.5513)	-1.2024**	(0.4899)
building land prices	0.0552**	(0.0266)	0.0014	(0.0310)	0.1665**	(0.0812)	0.0696	(0.0751)
accessibility (train)	-0.0708	(0.0495)	-0.0692	(0.0575)	-0.2646*	(0.1386)	-0.2937**	(0.1292)
accessibility (car)	-0.0601	(0.0894)	0.0408	(0.1060)	0.0699	(0.2728)	0.0405	(0.2529)
pop. density	-0.0018	(0.0018)	-0.0012	(0.0021)	-0.0008	(0.0061)	0.0009	(0.0057)
recreational area (per capita)	0.0274	(0.0218)	-0.0166	(0.0278)	0.1415**	(0.0691)	0.1169*	(0.0695)
public services	0.0049	(0.0395)	0.0866*	(0.0467)	-0.0171	(0.1244)	0.0883	(0.1094)
unemployment rate (π_{UO})	-0.6445	(0.5139)	-0.5321	(0.6318)	-3.1343*	(1.7299)	-3.0540*	(1.6715)
relative income control (w_0)	✓		✓		✓		✓	
constant	✓		✓		✓		✓	
observations	1842		1842		1842		1842	
df (model)	42		42		42		42	
F-statistic	8.69		3.65		8.75		7.06	
prob > F	0.0000		0.0000		0.0000		0.0000	
R-squared	0.1741		0.1012		0.1556		0.1445	
adjusted R-squared	0.1548		0.0802		0.1359		0.1246	

*** p<0.01, ** p<0.05, * p<0.1

Note: Statistical inference relies on robust standard errors. Measures of behavioural control (θ_R) and migration intention (θ_M) are accordingly conditioned, either with reference to an interstate or a cross-border move to another country in Europe. A concise model comparison is given in Table A6.8.

The sensitivity check yields directly interpretable significant coefficients as well: people who assess a certain move to be hardly risky at all expect on average a negative premium, yet not in the internal unemployment scenario. Moreover, the underlying item, directly addressing subjectively perceived riskiness of a specific form of mobility, absorbs more variation than the baseline risk variable, referring to individuals' willingness to take risks in the career domain.[116] Secondly, the less (more) inclined someone is to move within the first five years after graduation to a certain destination the higher (lower) the respective mobility premium.

Individual perceptions and intentions seem to matter when it comes to the formation of a subjective wage acceptance function. A direct implication is that labour market entrants, freshly graduated from university, who had no prior intention to move to another regional labour market, would ask for an especially high premium. This inflated premium is not related to social preferences, perceived riskiness of moving or high living standards at the current location – these factors are controlled for. Instead, it is attributable to an extremely pronounced place attachment amongst the future highly-skilled labour force, and hence, is required to overcome a sort of internal resistance against any form of migration behaviour.

Another result is worth mentioning, as coefficients of high levels of English proficiency are now smaller in size and insignificant. This is not contrary to the claim that English as *lingua franca* fosters successful socio-cultural or labour-market integration abroad, for the following reason: better English skills reduce the likelihood of post-migration hardships and transaction costs abroad, thus increase the likelihood of a successful migratory event. When controlling directly for expected riskiness of a move to another country, the related variation is no longer absorbed by the facilitator 'language skills', but by the corresponding control variable.

A second sensitivity check (B) addresses aspects of labour market readiness. Low levels of labour market readiness were associated with a lack of information on how employers value labour and qualifications. This could potentially translate into unrealistic wage expectations, and thus ex ante mobility premiums. Two groups displaying low degrees of labour market readiness come to mind: those respondents who have not yet gained any labour market experience and those who recently entered university, hence, have no urgent need to think actively about job search and form salary expectations. The opposite can be expected of those already being enrolled in a masters' programme, since they are likely to enter the labour market within the next two years. Additionally they already obtained a first university degree, which indicates a relatively advanced qualification level compared to their fellow students in a bachelor programme. To evaluate whether labour market experience might affect wage-related considerations, and thus the mobility premium, a vocational training variable is added. It is supplemented by a variable containing information on general labour market experience (full-time, part-time or mini-job and none). Those who already

[116] This item was implemented in the survey before participants were asked to state their wage expectations for various scenarios. Therefore, it is reasonable to assume that response behaviour in case of this item was not affected by the process of thinking about salary expectations. If respondents' subsequent answers, regarding expected wages for the alternative scenarios, were influenced by the previous assessment of a move's riskiness this would correspond to the model specification and appropriately mirror the decision-making process in this context.

gathered full-time working experience, and thereby received a payroll, might have a more realistic knowledge about how the labour market values their skills.

While neither the essential baseline results nor those from robustness check (A) change for the internal scenarios, labour market readiness is informative with respect to the process of forming wage expectations (Table A6.9 and Table A6.10). In the internal scenarios, those who already advanced to their masters' studies expect across labour market scenarios a 8.5 to 10 percentage point lower mobility premium. Previous work experience, however, does not influence individuals' expectations considering internal migration scenarios. This finding is reversed for the cross-border scenarios, where those with some work experience (part-time of mini-job) expect a significant positive premium in the try-your-luck scenario.

Sensitivity check (C) tests the hypothesis that some factors may be of differing importance for men and women. Whereas Table 6.5 reveals a significant gender difference regarding unconditional mobility premiums in the internal migration scenario, assuming unemployment, results from the sensitivity checks point to a more robust nature of this differential, also when controlling for other individual traits.

Table 6.5: Unconditional gender-specific mobility premiums

premium	female		male		t-test	KS
	mean	std.dev.	mean	std.dev.	p-value	p-value
Δ_{A1} (internal, given alternative job)	27.52	26.56	25.86	25.07	0.1496	0.218
Δ_{U1} (internal, given unemployment)	9.35	29.35	4.89	27.20	0.0004	0.004
Δ_{A2} (cross-border, given alternative job)	78.89	69.33	82.71	78.48	0.2562	0.509
Δ_{U2} (cross-border, given unemployment)	52.95	63.68	50.88	67.39	0.4855	0.170

Note: Sample comprises 854 female and 1183 male respondents and is conditional on the existence of all the four scenario specific premiums. The t-test tests for quality of group means. 'KS' refers to the Kolmogorov-Smirnov test for equality of distributions.

Sensitivity check (C) is based on gender subsamples, yielding for each scenario separate estimation equations and results (Table A6.11 and Table A6.12) for women and men. This approach allows investigating gender-specific patterns, without interpreting all results in reference to the other group. In order to identify significant differences regarding the relevance of one factor across the sexes, coefficient equality ($\beta^f = \beta^m$) is tested using a Wald test.[117]

Referring to the internal mobility scenarios, notable gender specific differences occur in three fields, namely those related to adjustment capability, social factors and local conditions. Adaptability to new circumstances is only relevant for women. On the other hand, only men expressing least pronounced preference for proximity to their family adjust their mobility premium downwards (-4.4 percentage points). A lack of accessibility of other metropolitan areas, higher per capita wealth levels or unemployment rates is only lowering men's expected mobility premiums. In the unemployment scenario, only least patient women expect a marked positive premium. The relevance of proximity to friends is exclusively relevant for men's mobility premiums.

[117] Results are reported in the last column in Table A6.11 and Table A6.12 (in the appendix).

Differing behaviour across the sexes becomes more prominent for the cross-border scenarios. The positive partnership premium is only observable for women and amounts to almost 15 percentage points. Similarly, women's mobility premiums are distinctly positive if they are most extraverted, least conscientious or adaptable to new circumstances. Moreover, Big-Five personality traits display typically only explanatory power in the female subsample. The most important factors shaping solely cross-border mobility premiums for men are the willingness to take risks and vocational training. Comparable to the internal migration scenarios, only men request to be compensated for potential changes in wealth levels, accessibility and employment perspectives.

Across all four scenarios, the mitigating impact of educational mobility on ex ante premiums is more pronounced within the female subsample. In contrast, men who spent some time abroad are also more willing to adjust their premium downwards. Regarding social factors, most pronounced preferences for proximity to family inflates especially women's mobility premiums. Yet, social factors are also non-negligible for men, since their preference for proximity to friends boosts all mobility premiums more than for their female peers.

6.6 Discussion and conclusion

Within recent years, related to a favourable development of the German labour market, recruitment attempts have become more challenging. On the one hand, the available local labour supply is more frequently inadequate to meet firms' requirements. On the other hand, salary demands of potential employees are more often perceived to be too high (IAB, 2016). Overall, this points to a more prevalent occurrence of mismatches between asking and offered wages. This may prolong the recruitment process, making hiring more costly. Ultimately, firms may refrain from filling some vacancies or creating new employment opportunities.

The pivotal point is the design of a compensation scheme, which is reasonable from an entrepreneurial perspective and sufficient to attract suitable employees from more distant labour markets. To achieve the latter, the compensation scheme might include a mobility premium. In this regard, the location of a hiring firm matters as well: some sought worker might be willing to move to a less favourable location only if a wage premium also compensated adequately for the associated drop in subjective well-being. Such possible interrelations between wages, location-specific amenities, and socio-demographic factors are intensively discussed in the literature on compensating differentials. Yet, personality or other individual traits, possibly acting as mobility facilitators, are typically not investigated.

This work explicitly takes into account a variety of individual traits, social preferences and adjustment capability. Using a student sample, comprising prospectively high-skilled employees, I examine which factors are involved in the formation of salary expectations under alternative migration and labour market scenarios. Moreover, these analyses highlight which prospective high-skilled workers might be especially costly to hire and which are most likely to refrain from applying for a distant job right away.

As others have shown before (cf. Clark and Cosgrove, 1991), derived mobility premiums in my analysis are connected to amenity levels, accessibility to other metropolitan areas, and labour market conditions at an individual's origin. However, psychic costs are even more important factors when it comes to the formation of an individual wage acceptance function, and hence, mobility premiums too. These psychic costs can explain why - even in an unemployment scenario - people expect on average a positive premium of 6.7 %.

Social ties are amongst the most prominent components, which increase psychic costs of leaving the familiar milieu: if someone exhibits the highest valuation of proximity to social reference persons, the ex ante mobility premium for an internal move increases between 6 percentage points (facing unemployment) and 13 percentage points (being employed). For corresponding cross-border moves to another European country, these individuals expect an additional premium of 27 percentage points to 34 percentage points. Typically, proximity to family is more valued by women and proximity to friends is more precious to men.

Within the process of forming salary expectations, personality and risk perception matter as well: least patient individuals expect a positive mobility premium; those perceiving a specific migratory path to be especially risky expect a further risk premium.

Another relevant trait is adjustment capability, likely to affect the costs of integrating into a new environment. Those least adaptable to new circumstances expect an additional mobility premium of around 3 percentage points. Among the factors contributing to an improved adjustment capability, especially previous mobility experiences are associated with lower expected mobility premiums: higher degrees of educational mobility in a geographic sense are associated across all types of scenarios with a dampening effect on ex ante mobility premiums. Those with international experience, who are more familiar with living abroad and have devised adjustment strategies, expect cross-border mobility premiums which are diminished by 10 to 17 percentage points. Yet the mobility fostering effect can also be observed in case of interstate mobility premiums, which are reduced by around four percentage points. Considering job-to-job mobility, individuals who participated during their adolescence in an exchange programme feature relatively lower mobility premiums. Referring to cross-border mobility premiums, there is also evidence in favour of a mobility facilitating effect of English language proficiency.

One of the main conclusions is that individually assessed (psychic) costs of mobility, though hard to measure, are highly relevant for understanding geographic mobility of high-skilled individuals: they have the potential to inflate expected mobility premiums, and thus, for a given wage offer distribution in an economy they may lower overall mobility. Some factors, scaling these costs up, cannot or should not be externally influenced, e.g., relevance of social ties. The impact of other factors, however, could be alleviated by fostering adjustment capability. This capability proves to be an especially promising leverage point and bears direct policy implications: promoting language proficiency is not only an investment into human capital, but into adjustment capabilities as well. One way to achieve this goal is to emphasise languages in the curriculum at schools or subsidising extra-curricular language courses, so they become more affordable for adolescents from less affluent families. In a similar manner, school exchange programmes should be further promoted, e.g., by facilitating the integration of individual short-term exchanges into the school year. Public funding, i.e., a sort of national ERASMUS for pupils, should additionally support exchange participation of children from lower-income families. Lastly, encouraging temporary sojourns abroad would allow future labour market entrants to familiarise with other labour markets or cultural peculiarities. This would not only increase socio-cultural capital in general, but the transferability of skills across borders as well. In addition, the increased adjustment capability could attenuate extremely high expected mobility premiums. Ultimately, not only intra-European and intra-national labour mobility could be fostered, but matching efficiency on regional labour markets as well.

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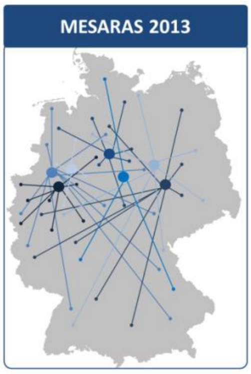
Appendix

Figure A2.1: MESARAS-survey questionnaire (translated version)

Mobility and preferences of students

Survey, winter term 2013/201



1 Miscellaneous

1.1 Gender

☐ male ☐ female

1.2 Age (in years)

________________ years

1.3 Number of siblings

☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ > 3

If you have one or more siblings: Are you the …

☐ oldest one ☐ youngest one ☐ neither nor

1.4 Place of birth

if in Germany: *please state PLZ (alternatively city and state)*
if abroad *please state the country*

____

1.5 Highest educational attainment

☐ A levels (Abitur) ☐ university degree

☐ vocational baccalaureate ☐ other: ____________________

1.6 Where did you obtain your university entrance certificate (e.g. Abitur)?

if in Germany: *please state PLZ (alternatively city and state)*
if abroad *please state the country*

____

1.7 In which year did you obtain your university entrance certificate?

____

1.8 Which average grade did you attain in your university entrance certificate (e.g. Abitur)?

____

1.9 Mother's highest educational attainment

☐ lower secondary education (Hauptschule) ☐ secondary education (Realschulabschluss)

☐ A levels (auch Fachabitur) ☐ university degree (inc. University of applied sciences)

☐ none ☐ other: ____________________

1.10 Father's highest educational attainment

☐ lower secondary education (Hauptschule) ☐ secondary education (Realschulabschluss)

☐ A levels (auch Fachabitur) ☐ university degree (inc. University of applied sciences)

☐ none ☐ other: ____________________

1.11 Are you currently in a relationship?

☐ no ☐ yes

If yes, for how long have you been in this relationship?

☐ < 6 months ☐ 6-12 months ☐ 1-2 years ☐ 2-3 years ☐ > 3 years

1.12 Did you complete any vocational training?

☐ no ☐ yes, the following: ____________________________

1.13 Did you work in one (or several) **of the following employment relationships before your current study programme?**
(multiple responses allowed)

☐ full-time (100%) ☐ part-time (< 100%, mehr als Minijob) ☐ Minijob, temporary help (e.g. on 450 Euro-basis) ☐ no

2 Mobility

2.1 Did you still live at the place of birth when you enrolled in elementary school?

☐ yes ☐ no

if other location in Germany: *please state PLZ (alternatively city and state)*
if other location abroad: *please state the country*

____

2.2 How often did you change your place of residence <u>during school years</u>?

☐ not once ☐ once *(only **A**)* ☐ twice *(only **A** and **B**)* ☐ three times *(**A**, **B** and **C**)* ☐ more than three times *(**A**, **B** and **C**)*

A If you changed your place of residence **at least once** during school years, please state the new location of your **last** residence change.
if in Germany: PLZ or city and state
if abroad: country
____

B If you changed your place of residence **at least twice** during school years, please state the new location of your **penultimate** residence change.
if in Germany: PLZ or city and state
if abroad: country
____

C If you changed your place of residence **at least three times** during school years, please state the new location of your **antepenultimate** residence change.
if in Germany: PLZ or city and state
if abroad: country
____

2.3 How often did you change your palce of residence <u>after completion of your school years</u>?

☐ not once ☐ once *(only **A**)* ☐ twice *(only **A** and **B**)* ☐ three times *(**A**, **B** and **C**)* ☐ more than three times *(**A**, **B** and **C**)*

A If you changed your place of residence **at least once** after completion of your school years, please state the new location of your **last** residence change.
if in Germany: PLZ or city and state
if abroad: country
____

B If you changed your place of residence **at least twice** after completion of your school years, please state the new location of your **penultimate** residence change.
if in Germany: PLZ or city and state
if abroad: country
____

C If you changed your place of residence **at least three times** after completion of your school years, please state the new location of your **antepenultimate** residence change.
if in Germany: PLZ or city and state
if abroad: country
____

2.4 Did you participate in a school exchange programme during your school years?
(usually a one or two week mutual exchange)

☐ no ☐ yes, in the following country ___________________

2.5 Did you spent in the past a considerable time (more than one month) **without your family abroad?**
(multiple responses allowed)

☐ yes, as part of a semester abroad during school or studies Country: ______________
☐ yes, within an internship abroad or as "Au-Pair" Country: ______________
☐ yes, work-related (if you have been previously employed) Country: ______________
☐ yes, within "Work and Travel" Country: ______________
☐ yes, for another reason: ____________________ Country: ______________
☐ no

2.6 In your opinion, which would be the most severe obstacle to a move to another country?

___

3 Studies

3.1 Please state your current study programme.

___

3.2 Which type of study programme is it?

☐ Bachelor ☐ Master ☐ other: ___

3.3 In which semester are you currently?

___ study semester *(semesters enroled in your current programme)*

___ university semester *(total number of semesters enroled at higher education institutions)*

3.4 Do you intend to enrol in a consecutive study programme after completion of your current study programme?

☐ no ☐ yes ☐ perhaps

3.5 Are you planning on studying one semester abroad during studies?

☐ no ☐ yes ☐ perhaps

If yes or perhaps, what would be your preferred destination country?

___

3.6 Did you apply for an economics programme at other higher education institutions in the winter term 2013/2014?

☐ no ☐ yes

If yes, please state these higher education institutions in your preferred order.

Institution 1: ___

Institution 2: ___

Institution 3: ___

In the winter term 2013/2014, did you obtain at other higher education institutions admission to an economics programme?

☐ no ☐ yes

If yes, please state these higher education institutions in your preferred order.

Institution 1: ___

Institution 2: ___

Institution 3: ___

3.7 Did you apply for any other programme at other higher education institutions in the winter term 2013/2014?

☐ no ☐ yes

If yes, please state these higher education institutions in your preferred order.

Institution 1: ___

Institution 2: ___

Institution 3: ___

In the winter term 2013/2014, did you obtain at other higher education institutions admission to any other programme?

☐ no ☐ yes

If yes, please state these higher education institutions in your preferred order.

Institution 1: ___

Institution 2: ___

Institution 3: ___

3.8 Is your current study programme the preferred one?

☐ no ☐ yes

3.9 Is your current university the preferred one?

☐ no ☐ yes

3.10 Is the current university the closest university (higher education institution) **in relation to your place of residence immediately before enrolment?**

☐ no ☐ yes ☐ don't know

3.11 How important were the following aspects concerning your decision for studying at your current university?

reputation of university / department	very unimportant	☐	☐	☐	☐	☐	☐	☐	very important
curriculum (programme features)	very unimportant	☐	☐	☐	☐	☐	☐	☐	very important
ressources of university / department	very unimportant	☐	☐	☐	☐	☐	☐	☐	very important
proximity to previous palce of residence	very unimportant	☐	☐	☐	☐	☐	☐	☐	very important
friends study / live here as well	very unimportant	☐	☐	☐	☐	☐	☐	☐	very important
living costs	very unimportant	☐	☐	☐	☐	☐	☐	☐	very important
interest in city	very unimportant	☐	☐	☐	☐	☐	☐	☐	very important
admission criteria	very unimportant	☐	☐	☐	☐	☐	☐	☐	very important
availability of accomodation	very unimportant	☐	☐	☐	☐	☐	☐	☐	very important

3.12 Did you already find an accommodation, you would like to stay in for some semesters?

☐ no ☐ yes

3.13 Please state the postal code of your current place of residence.

PLZ: ______________________ *(if PLZ unknown, please state city and state)*

3.14 In which housing situation are you currently living?

☐ parental home ☐ private flat share

☐ student dorm ☐ own (rented) flat (alone or with partner) ☐ other: ______________

3.15 How long does it take you to reach your university (your campus) **from your current residence?**

☐ < 10 minutes ☐ 10 - 20 minutes ☐ 20 - 30 minutes

☐ 30 - 45 minutes ☐ 45 - 60 minutes ☐ 60 - 90 minutes

☐ 90 - 120 minutes ☐ > 120 minutes

3.16 What are your monthly accommodation costs (inlcuding all known service charges)**?**

______________ Euro

3.17 Which sum do you have at your disposal - after deduction of your accommodation costs - for your livelihood per month?

______________ Euro

3.18 How do you intend to finance the current semester?

(Please state the approximate share. The sum has to add up to 100%.)

	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
parents	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
working	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
own saving	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
BAFöG	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
student loan	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
scholarship	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
other: ______________	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
row sum	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

4 Preferences and valuations

4.1 To what extent do the following statements apply?

Moving to another town (in the same state) is a risky endeavour.	applies not at all	☐	☐	☐	☐	☐	☐	☐	applies completely
Moving to another state is a risky endeavour.	applies not at all	☐	☐	☐	☐	☐	☐	☐	applies completely
Moving to another country within Europe is a risky endeavour.	applies not at all	☐	☐	☐	☐	☐	☐	☐	applies completely
Moving to another country outside Europe is a risky endeavour.	applies not at all	☐	☐	☐	☐	☐	☐	☐	applies completely

Below, you will have the choice between two alternative payoffs.
Please state <u>for each row</u>, whether you chose option A or option B.

4.2

Option A: You have a 50:50 CHANCE either to receive			Option B: You receive ANYWAY
0 € or 10 €	☐	☐	0 €
0 € or 10 €	☐	☐	1 €
0 € or 10 €	☐	☐	2 €
0 € or 10 €	☐	☐	3 €
0 € or 10 €	☐	☐	4 €
0 € or 10 €	☐	☐	5 €
0 € or 10 €	☐	☐	6 €
0 € or 10 €	☐	☐	7 €
0 € or 10 €	☐	☐	8 €
0 € or 10 €	☐	☐	9 €
0 € or 10 €	☐	☐	10 €

4.3

Option A: You have a 50:50 CHANCE either			Option B: You receive ANYWAY
to pay 4 € or to receive 10 €	☐	☐	0 €
to pay 4 € or to receive 10 €	☐	☐	1 €
to pay 4 € or to receive 10 €	☐	☐	2 €
to pay 4 € or to receive 10 €	☐	☐	3 €
to pay 4 € or to receive 10 €	☐	☐	4 €
to pay 4 € or to receive 10 €	☐	☐	5 €
to pay 4 € or to receive 10 €	☐	☐	6 €
to pay 4 € or to receive 10 €	☐	☐	7 €
to pay 4 € or to receive 10 €	☐	☐	8 €
to pay 4 € or to receive 10 €	☐	☐	9 €
to pay 4 € or to receive 10 €	☐	☐	10 €

4.4

Option A: You receive the following amount TODAY			Option B: You receive the following amount IN ONE MONTH
10 €	☐	☐	10 €
10 €	☐	☐	11 €
10 €	☐	☐	12 €
10 €	☐	☐	13 €
10 €	☐	☐	14 €
10 €	☐	☐	15 €
10 €	☐	☐	16 €
10 €	☐	☐	17 €
10 €	☐	☐	18 €
10 €	☐	☐	19 €
10 €	☐	☐	20 €

4.5 **Option A: You receive the following amount <u>IN ONE MONTH</u>** | **Option B: You receive the following amount <u>IN TWO MONTHS</u>**

Option A			Option B
10 €	☐	☐	10 €
10 €	☐	☐	11 €
10 €	☐	☐	12 €
10 €	☐	☐	13 €
10 €	☐	☐	14 €
10 €	☐	☐	15 €
10 €	☐	☐	16 €
10 €	☐	☐	17 €
10 €	☐	☐	18 €
10 €	☐	☐	19 €
10 €	☐	☐	20 €

4.6 **How certain do you feel that you would behave in a real situation accordingly to your statements in the last four questions?**

very uncertain ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ very certain

4.7 **Which amount would you request as a payoff <u>in one month</u> so you would be willing to forego <u>today</u> a payoff of 1000 Euro?**

____________________ Euro

4.8 **How would you see yourself: Are you in general willing to take risks, or do you try to avoid risks?**

not at all willing to take risks ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ highly willing to take risks

4.9 **How would you assess your willingness to take risks in the following domains?**

driving	not at all willing to take risks	☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐	highly willing to take risks
financial matters	not at all willing to take risks	☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐	highly willing to take risks
leisure and sports	not at all willing to take risks	☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐	highly willing to take risks
career aspects (your studies)	not at all willing to take risks	☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐	highly willing to take risks
health aspects	not at all willing to take risks	☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐	highly willing to take risks
trusting other persons	not at all willing to take risks	☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐	highly willing to take risks
new experiences	not at all willing to take risks	☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐	highly willing to take risks

4.10 **Imagine you won a prize of 1000 Euro from a local bank. You have now the choice between either to take the money with you right away or to invest it for one year at the bank. Which interest rate would you request, so you would be willing to leave the money at the bank?**

____________________ per cent

5 Expectations

5.1 **What would be the <u>minimum monthly net income</u>* you expect to receive after you eventually will have graduated from university?**

*(*corresponds to the income after taxes and social insurance contributions have been deducted)*

____________________ Euro

5.2 **How would you rate your income after you finally graduated from university in relation to the income of your …**

… mother?	distinctly lower	☐ ☐ ☐ ☐ ☐ ☐ ☐	distinctly higher	☐	don't know
… father?	distinctly lower	☐ ☐ ☐ ☐ ☐ ☐ ☐	distinctly higher	☐	don't know

5.3 **Imagine, that after graduation, you will receive an interesting job offer in the vicinity of your current residence, realising the monthly net income you expect** (see Question 5.1).

What would be the <u>minimum</u> monthly net income for an otherwise comparable job offer, which made you willing to move for this alternative job to an unfamilar environment:

to another state ____________________ Euro per month (net)

to another country ____________________ Euro per month (net)

5.4 In your opinion, how likely is it that you will move within five years after you graduated from university?

within town	highly unlikely	☐	☐	☐	☐	☐	☐	☐	highly likely
to another town in the same state	highly unlikely	☐	☐	☐	☐	☐	☐	☐	highly likely
to another state	highly unlikely	☐	☐	☐	☐	☐	☐	☐	highly likely
to another country in Europe	highly unlikely	☐	☐	☐	☐	☐	☐	☐	highly likely
to another country outside Europe	highly unlikely	☐	☐	☐	☐	☐	☐	☐	highly likely

5.5 Please state, how far you would be willing to move for the following aspects.

(within the state < to another state < to another European country < to a country outside Europe)

	not willing to move at all	within the state	to another state	to another European country	to a country outside Europe
larger proximity to family or friends	☐	☐	☐	☐	☐
better income opportunities (higher income)	☐	☐	☐	☐	☐
better housing conditions	☐	☐	☐	☐	☐
new living environment	☐	☐	☐	☐	☐
better infrastructure	☐	☐	☐	☐	☐
better employment chances when unemployed	☐	☐	☐	☐	☐
climatic preferences	☐	☐	☐	☐	☐

5.6 Imagine, that despite intensive job search after graduation, you will NOT receive an interesting job offer in the vicinity of your current residence, realising the monthly net income you expect (see Question 5.1).

What would be the minimum monthly net income for a job offer you were interested in, which made you willing to move for this alternative job to an unfamilar environment:

to another state ____________________ Euro per month (net)

to another country ____________________ Euro per month (net)

6 Self-assessment

6.1 Please think of your university entrance certificate. How would you rate your average grade in relation to your …

… school cohort?	strongly below average	☐	☐	☐	☐	☐	☐	☐	strongly above average
… fellow students in your programme?	strongly below average	☐	☐	☐	☐	☐	☐	☐	strongly above average

6.2 In relation to your fellow students, how do you expect to graduate from university?

strongly below average ☐ ☐ ☐ ☐ ☐ ☐ ☐ strongly above average

6.3 To what extent do the following statements apply? I see myself as someone who …

… is reserved	applies not at all	☐	☐	☐	☐	☐	applies completely
… is generally trusting	applies not at all	☐	☐	☐	☐	☐	applies completely
… tends to be lazy	applies not at all	☐	☐	☐	☐	☐	applies completely
… is relaxed, handles stress well	applies not at all	☐	☐	☐	☐	☐	applies completely
… has few artictic interests	applies not at all	☐	☐	☐	☐	☐	applies completely
… is outgoing, sociable	applies not at all	☐	☐	☐	☐	☐	applies completely
… tends to find fault with outhers	applies not at all	☐	☐	☐	☐	☐	applies completely
… does a thorough job	applies not at all	☐	☐	☐	☐	☐	applies completely
… gets nervous easily	applies not at all	☐	☐	☐	☐	☐	applies completely
… has an active imgaination	applies not at all	☐	☐	☐	☐	☐	applies completely

6.4 Imagine you had the choice between either going to the cinema or meeting with fellow students in the university library to learn together. Please mark for consistency reasons, independently from the initial situation, both the outmost left and the outmonst right check box.

I can easily chose between these alternatives. applies not at all ☐ ☐ ☐ ☐ ☐ applies completely

6.5 How often do you go out with your friends per week?

☐ less than once ☐ once ☐ twice
☐ three times ☐ more than three times

6.6 How often are you active on Facebook or other social networks?

☐ several times a day ☐ once a day ☐ several times a week
☐ once a week ☐ less frequent ☐ never

6.7 How do you see yourself regarding the following aspects?

I have a hard time adjusting to new circumstances.	applies not at all	☐	☐	☐	☐	☐	☐	☐	applies completely
I am willing to bear costs in the present, so I can benefit from related benefits in the future.	applies not at all	☐	☐	☐	☐	☐	☐	☐	applies completely
I would like to live or work abroad later in my life.	applies not at all	☐	☐	☐	☐	☐	☐	☐	applies completely
Spatial proximity to my family plays an important role for me.	applies not at all	☐	☐	☐	☐	☐	☐	☐	applies completely
Spatial proximity to my friends plays an important role for me.	applies not at all	☐	☐	☐	☐	☐	☐	☐	applies completely
I am a patient person.	applies not at all	☐	☐	☐	☐	☐	☐	☐	applies completely

6.8 How would you rate your language proficiencies?

<u>business fluent</u>: *You are able to to discuss and understand complex topics and details in the respective language.*

<u>fluent in daily routine</u>: *You are able to get along and communicate without problems in daily life with your vocabulary.*

<u>basic</u>: *You have a basic language proficiency, however, speaking fluently or understanding details remains a substantial challenge.*

	mother tongue	business fluent	fluent in daily routine	basic
German	☐	☐	☐	☐
English	☐	☐	☐	☐
other language:____________	☐	☐	☐	☐
other language:____________	☐	☐	☐	☐
other language:____________	☐	☐	☐	☐

6.9 How do you assess yourself / the following statements?

If someone treats you unfarily, it is legit to reciprocate this unfairness.	applies not at all	☐	☐	☐	☐	☐	☐	☐	applies completely
Since you cannot expect fairness from a stranger, I sometimes treat an unknown person in an unfair manner.	applies not at all	☐	☐	☐	☐	☐	☐	☐	applies completely

6.10 There are different demographic groups, some closer to the top and others closer to the bottom of our society. Thinking of yourself, where would you locate yourself on such a scale …

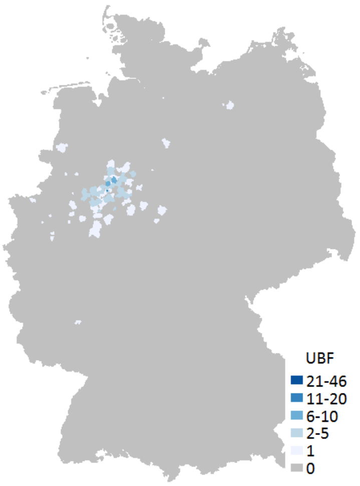
… in comparison to the overall society?		… in comparison to your immediate social environment?	
	top		top
	☐		☐
	☐		☐
	☐		☐
	☐		☐
	☐		☐
	☐		☐
	☐		☐
	bottom		bottom

Thank you for your participation.

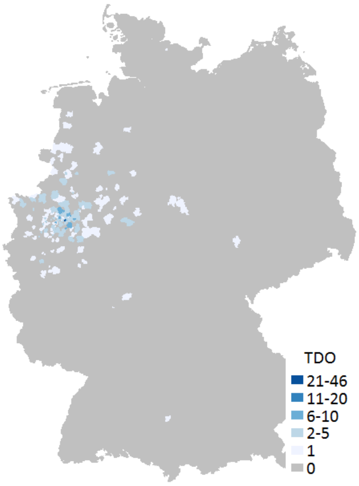
Please wait until the persons sitting beside you have finished as well. You then may pass through all questionnaires.

Figure A2.2: Catchment area of participating universities (primary target group)

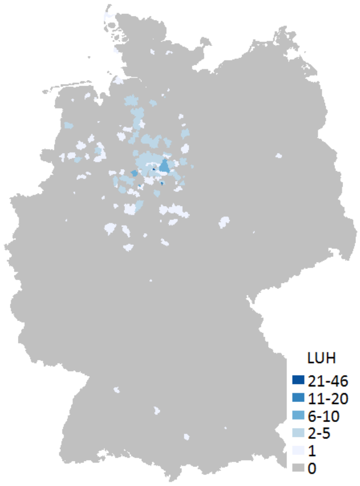
Bielefeld



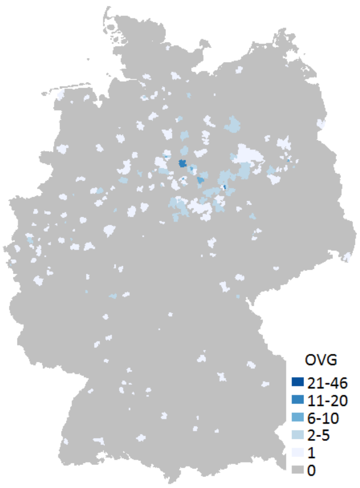
Dortmund



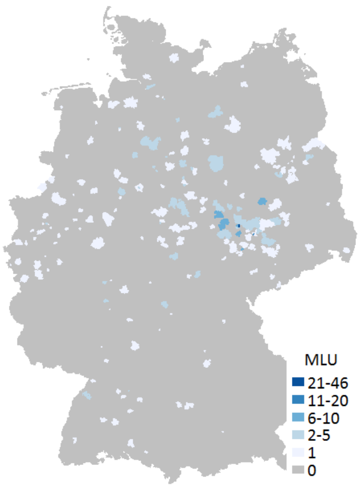
Hannover



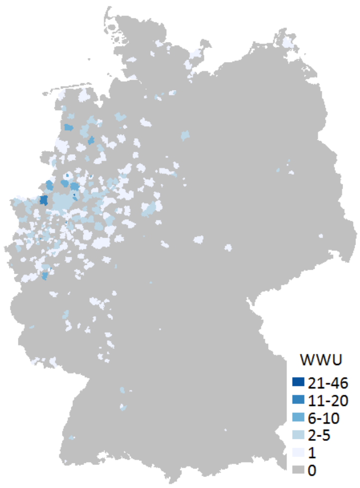
Magdeburg



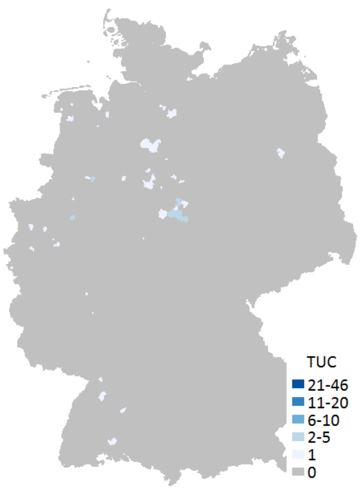
Halle / Saale



Muenster



Clausthal-Zellerfeld



Note: The graphs illustrate the frequency a postal code area has been identified as a respondent's origin.

Table A3.1: Descriptive statistics for dependent variables

section	variable label	short description	scale	N	min	max	mean	std.dev.
choice set's scope	b_{i,C_0}	1 if several applications, 0 otherwise	binary	1717	0	1	0.78	-
	n_{i,C_0}	number of applications, censored at 4	ordinal	1717	1	4	-	-
	b^L_{i,C_0}	1 if several applications at distinct locations, 0 otherwise	binary	1717	0	1	0.78	-
	n^L_{i,C_0}	number of applications at distinct locations, censored at 4	ordinal	1717	0	4	-	-
choice set's components	d^{min}_{i,C_0}	excess distance of closest application	km, cardinal	1714	0	439.1	42.76	70.92
	d^{avg}_{i,C_0}	average excess distance of all applications	km, cardinal	1714	0	482.8	100.42	94.58
	r^{avg}_{d,i,C_0}	excess distance of remotest application	km, cardinal	1714	0	680.0	169.05	150.73
observed mobility	$u_i \| n^*_{i,C_1} = 2$	1 if chosen university is not closest compared to the most preferred alternative with admission, 0 else	binary	1053	0	1	0.34	-
	$u_i \| n^{L*}_{i,C_1} = 2$	1 if chosen university is not closest compared to the most preferred geographically distinct alternative with admission, 0 else	binary	1053	0	1	0.37	-
	$u_i \| n^*_{i,C_1} \in [2,4]$	1 if chosen university is not closest compared to three most preferred alternatives with admission, 0 else	binary	1053	0	1	0.53	-
	$r_u \| n^*_{i,C_1} \in [2,4]$	1 if chosen university was the closest alternative with admission, 2 if it was neither the closest nor the remotest alternative, 3 if it was the remotest alternative	ordinal	1053	1	3	-	-
robustness checks: alternative distance concepts	$u_i \| n^*_{i,C_1} = 2$ (road)	1 if chosen university is not closest (based on road distance) compared to the most preferred alternative with admission, 0 else	binary	1053	0	1	0.34	-
	$u_i \| n^*_{i,C_1} = 2$ (travel time)	1 if chosen university is not closest (based on travel time in minutes) compared to the most preferred alternative with admission, 0 else	binary	1053	0	1	0.35	-

Note: Observed mobility measures are based on a simple distance measure, representing geographic distance between origin (place where the university entrance certificate was obtained) and a location of interest. The concept of 'excess distance' refers always to the difference between simple distance and the distance from origin to the closest potential alternative. Means are only depicted for non-ordinal variables; standard deviations only for cardinal variables.

Table A3.2: Descriptive statistics for explanatory variables

category	variable label	short description	original scale	N	min	max	mean	std. dev.	modified scale
socio-demographic	*gender*	1: female, 0: male	binary	1717	0	1	0.56	-	
	age	age in years	cardinal	1717	17	45	19.71	1.80	
	academic household	1: at least one parent is academic, 0: no parent is academic	binary	1717	0	1	0.43	-	
	uec grade	average grade of uec entrance certificate (best grade: 1.0, worst grade: 4.0)	cardinal	1717	1	3.8	2.31	0.58	
	vocational training	1: vocational training completed, 0: otherwise	binary	1717	0	1	0.15	-	
	partnership	0: no relationship, 1: < 6 months, 2: 6-12 months, 3: 1-2 years, 4: 2-3 years, 5: > 3 years	ordinal	1717	0	5	-	-	
previous mobility experiences	*residential move during school*	1: at least one residential move during school, 0: none	binary	1717	0	1	0.22	-	
	exchange participation	1 : exchange participation during school, 0 : otherwise	binary	1717	0	1	0.34	-	
individual traits / personality	*Big-Five: extraversion*	5-point scale (1: low, 5: high)	ordinal	1717	1	5	3.42	0.97	✓
	Big-Five: neuroticism	5-point scale (1: low, 5: high)	ordinal	1717	1	5	2.83	0.91	✓
	Big-Five: openness	5-point scale (1: low, 5: high)	ordinal	1717	1	5	3.20	1.03	✓
	Big-Five: conscientiousness	5-point scale (1: low, 5: high)	ordinal	1717	1	5	3.42	0.89	✓
	Big-Five: agreeableness	5-point scale (1: low, 5: high)	ordinal	1717	1	5	2.96	0.80	✓
	risk attitude (career domain)	willingness to take risks in the career domain, 11-point scale (1: low, 11: high)	ordinal	1717	1	11	5.39	2.42	✓
	patience	willingness to bear costs in the present for future benefits, 7-point scale (1: low, 7: high)	ordinal	1717	1	7	5.44	1.17	✓
	importance of proximity (family)	7-point scale (1: low, 7: high)	ordinal	1717	1	7	4.81	1.63	✓
	adaptability	ability to adapt to new circumstances, 7-point scale (1: low, 7: high)	ordinal	1717	1	7	4.93	1.53	✓
distance deterrence	*distance to closest alternative (2)*	distance to the closer alternative, either chosen university or most preferred (but not chosen) alternative	km, cardinal	1717	0	484.8	80.50	89.92	
	distance to closest alternative (4)	distance to the closest alternative, among the chosen university or the three most preferred (but not chosen) alternatives	km, cardinal	1717	0	481.5	68.84	82.13	
local conditions at origin	*GDP growth*	INKAR 2012 data, reference year 2007	%	1717	-14	31.4	10.23	6.10	
	unemployment growth	INKAR 2012 data, reference year: 2007	%	1717	-7.4	-0.10	-2.01	1.15	
	population density (log)	INKAR 2012 data	log	1717	3.61	8.40	6.07	1.05	
	recreational area (per capita, log)	INKAR 2012 data	log	1717	2.83	5.94	3.85	0.55	

Note: Reported descriptive statistics refer to the largest analytical sample, taken from the scope approach. 'Original scale' refers to the scale the information has been elicited from survey participants. Modified variables have been standardised and categorised into three distinct groups: those scoring low (score below the mean minus one standard deviation), the reference group of medium-type individuals (score within the range of one standard deviation around the mean) and those scoring high (score more than one standard deviation above the mean). INKAR data originates from the INKAR online database (http://www.inkar.de/), provided by the Federal Institute for Research on Building, Urban Affairs and Spatial Development (BBSR, 2014).

Table A3.3: Choice set's scope – binary approach, applications to geographically distinct locations

dependent variable	b^L_{i,C_0}		b^L_{i,C_0}				b^L_{i,C_0}			
estimation method	logit		LPM		IV (2nd stage)		LPM		IV (2nd stage)	
	OR	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.
gender (female)	1.2485	(0.1713)	0.0322	(0.0212)	0.0006	(0.0354)	0.0165	(0.0217)	-0.0334	(0.0417)
age	0.8312***	(0.0401)	-0.0319***	(0.0088)	-0.0362***	(0.0093)	-0.0264***	(0.0086)	-0.0318***	(0.0095)
academic household	1.1833	(0.1527)	0.0267	(0.0201)	0.0303	(0.0291)	0.0226	(0.0204)	0.0248	(0.0326)
uec grade	0.7795**	(0.0955)	-0.0374*	(0.0199)	-0.0522*	(0.0301)	-0.0641***	(0.0198)	-0.0971***	(0.0360)
vocational training	1.4682	(0.3553)	0.0669	(0.0414)	0.0672	(0.0476)	0.0666	(0.0409)	0.0675	(0.0520)
partnership										
< 6 months	1.3220	(0.3539)	0.0365	(0.0349)	-0.0010	(0.0478)	0.0343	(0.0358)	-0.0239	(0.0558)
6-12 months	0.8259	(0.1833)	-0.0296	(0.0382)	-0.0762	(0.0555)	-0.0470	(0.0391)	-0.1193*	(0.0650)
1-2 years	0.7252	(0.1520)	-0.0555	(0.0374)	-0.0630	(0.0535)	-0.0636*	(0.0382)	-0.0722	(0.0588)
2-3 years	1.0698	(0.2389)	0.0093	(0.0341)	0.0108	(0.0430)	0.0076	(0.0357)	0.0111	(0.0497)
> 3 years	1.1664	(0.2936)	0.0199	(0.0382)	0.0029	(0.0483)	0.0194	(0.0395)	-0.0064	(0.0553)
risk attitude (career domain)										
score $< \mu - \sigma$	1.0489	(0.2012)	0.0089	(0.0289)	0.0097	(0.0359)	0.0164	(0.0302)	0.0215	(0.0420)
score $> \mu + \sigma$	0.7631*	(0.1166)	-0.0443*	(0.0252)	-0.0353	(0.0372)	-0.0398	(0.0253)	-0.0275	(0.0421)
patience										
score $< \mu - \sigma$	0.5664***	(0.0873)	-0.0997***	(0.0287)	-0.1026***	(0.0314)	-0.0981***	(0.0295)	-0.1003***	(0.0350)
score $> \mu + \sigma$	1.3145	(0.2460)	0.0409	(0.0261)	0.0144	(0.0482)	0.0366	(0.0261)	-0.0098	(0.0552)
extraversion										
score $< \mu - \sigma$	0.8361	(0.1542)	-0.0325	(0.0325)	0.0410	(0.0879)	-0.0457	(0.0334)	0.0737	(0.1005)
score $> \mu + \sigma$	0.9481	(0.1505)	-0.0080	(0.0250)	-0.0597	(0.0529)	-0.0101	(0.0255)	-0.0955	(0.0634)
neuroticism										
score $< \mu - \sigma$	0.8169	(0.1625)	-0.0339	(0.0324)	-0.1058	(0.0679)	-0.0298	(0.0325)	-0.1416*	(0.0781)
score $> \mu + \sigma$	0.8804	(0.1562)	-0.0192	(0.0281)	0.0207	(0.0488)	-0.0110	(0.0285)	0.0560	(0.0573)
openness										
score $< \mu - \sigma$	0.9284	(0.1460)	-0.0131	(0.0253)	-0.0120	(0.0332)	-0.0066	(0.0260)	-0.0015	(0.0372)
score $> \mu + \sigma$	0.9533	(0.1612)	-0.0077	(0.0269)	-0.0162	(0.0331)	-0.0333	(0.0272)	-0.0531	(0.0388)
conscientiousness										
score $< \mu - \sigma$	0.9492	(0.1483)	-0.0107	(0.0262)	0.0075	(0.0315)	-0.0093	(0.0269)	0.0182	(0.0358)
score $> \mu + \sigma$	0.8927	(0.1537)	-0.0184	(0.0259)	-0.0454	(0.0356)	-0.0219	(0.0265)	-0.0658	(0.0412)
agreeableness										
score $< \mu - \sigma$	1.0113	(0.1580)	-0.0005	(0.0252)	0.0286	(0.0353)	-0.0111	(0.0261)	0.0296	(0.0405)
score $> \mu + \sigma$	1.0701	(0.1840)	0.0091	(0.0263)	-0.0190	(0.0350)	0.0088	(0.0271)	-0.0354	(0.0410)
x_1^{endog}: imp. of prox. (family)	1.0321	(0.0418)	0.0049	(0.0063)	0.0848	(0.0725)	0.0028	(0.0063)	0.1188	(0.0844)
x_2^{endog}: adaptability	1.1642***	(0.0524)	0.0242***	(0.0074)	0.1360	(0.0960)	0.0213***	(0.0076)	0.1998*	(0.1138)
origin controls	✓		✓		✓					
constant	✓		✓		✓		✓		✓	
observations	1717		1717		1717		1717		1717	
log likelihood	-834.45									
df	30		30		30		26		26	
LR χ^2(df) / F(df)	124.95		4.78		118.97		3.07		54.76	
prob > χ^2/ prob > F	0.0000		0.0000		0.0000		0.0000		0.0008	
pseudo R^2 / adjusted R^2	0.0793		0.0689				0.0304			
exogeneity test										
Wooldridge (1995) score test					2.18 (p=0.3383)				4.30 (p=0.1166)	
regression based test					1.06 (p=0.3453)				2.12 (p=0.1203)	
1st stage: x_1^{endog}										
F(model)					6.51 (p=0.0000)				7.14 (p=0.0000)	
z_1: res. move during school					-0.3671 ***	(0.0976)			-0.3568 ***	(0.0972)
z_2: exchange participation					-0.1225	(0.0820)			-0.1278	(0.0814)
F(instruments)					8.38 (p=0.0002)				8.18 (p=0.0004)	
1st stage: x_2^{endog}										
F(model)					13.54 (p=0.0000)				15.08 (p=0.0000)	
z_1: res. move during school					0.0068	(0.0857)			0.0143	(0.0857)
z_2: exchange participation					0.2505 ***	(0.0744)			0.2421 ***	(0.0742)
F(instruments)					5.71 (p=0.0034)				5.36 (p=0.0048)	
weak instrument test										
F^{crit} ($\alpha = 0.10$)					7.03				7.03	
F^{crit} ($\alpha = 0.15$)					4.58				4.58	
F^{crit} ($\alpha = 0.20$)					3.95				3.95	

*** p<0.01, ** p<0.05, * p<0.1

Note: The two potentially endogenous variables (importance of proximity to family and adaptability to new circumstance) enter the specifications as quasi continuous variables (on a scale from 1 to 7). This modification is implemented with regard to the first stage estimations. F^{crit} report the critical values of Stock and Yogo's (2005) weak instrument test, assuming i.i.d. error structure.

Table A3.4: Choice set's scope – ordinal approach, applications to geographically distinct locations

dependent variable	n^{L}_{i,C_0}		n^{L}_{i,C_0}		n^{LP}_{i,C_0}		n^{LP}_{i,C_0}	
estimation method	ologit		ologit		cpoisson		cpoisson	
	OR	s.e.	OR	s.e.	IRR	s.e.	IRR	s.e.
gender (female)	1.1586	(0.1182)	1.0686	(0.1078)	1.0694	(0.0496)	1.0360	(0.0480)
age	0.8740***	(0.0325)	0.9034***	(0.0318)	0.9389 ***	(0.0168)	0.9530 ***	(0.0163)
academic household	1.1614	(0.1118)	1.1277	(0.1064)	1.0630	(0.0459)	1.0588	(0.0458)
uec grade	0.9847	(0.0918)	0.8560*	(0.0774)	0.9915	(0.0417)	0.9261 *	(0.0377)
vocational training	1.2579	(0.2292)	1.2483	(0.2189)	1.1080	(0.0948)	1.1058	(0.0934)
partnership								
< 6 months	0.8762	(0.1395)	0.8645	(0.1367)	0.9531	(0.0715)	0.9392	(0.0714)
6-12 months	0.8065	(0.1416)	0.7228*	(0.1273)	0.8990	(0.0748)	0.8525 *	(0.0715)
1-2 years	0.8008	(0.1374)	0.7502*	(0.1290)	0.8893	(0.0720)	0.8670 *	(0.0704)
2-3 years	0.8543	(0.1336)	0.8695	(0.1363)	0.9448	(0.0693)	0.9402	(0.0708)
> 3 years	0.7562*	(0.1267)	0.7613*	(0.1245)	0.8779	(0.0720)	0.8779	(0.0725)
risk attitude (career domain)								
score $< \mu - \sigma$	0.9875	(0.1376)	1.0464	(0.1455)	1.0007	(0.0635)	1.0241	(0.0657)
score $> \mu + \sigma$	0.8560	(0.1020)	0.8836	(0.1025)	0.9265	(0.0506)	0.9425	(0.0511)
patience								
score $< \mu - \sigma$	0.6328***	(0.0799)	0.6474***	(0.0817)	0.8030 ***	(0.0495)	0.8118 ***	(0.0506)
score $> \mu + \sigma$	1.1525	(0.1447)	1.1319	(0.1396)	1.0733	(0.0603)	1.0648	(0.0596)
extraversion								
score $< \mu - \sigma$	0.6156***	(0.0871)	0.6147***	(0.0856)	0.7989 ***	(0.0558)	0.7880 ***	(0.0554)
score $> \mu + \sigma$	1.0527	(0.1243)	1.0311	(0.1207)	1.0265	(0.0552)	1.0147	(0.0547)
neuroticism								
score $< \mu - \sigma$	0.9269	(0.1393)	0.9470	(0.1395)	0.9569	(0.0670)	0.9707	(0.0678)
score $> \mu + \sigma$	1.0834	(0.1483)	1.1113	(0.1502)	1.0413	(0.0631)	1.0560	(0.0637)
openness								
score $< \mu - \sigma$	0.9104	(0.1082)	0.9444	(0.1115)	0.9597	(0.0527)	0.9719	(0.0538)
score $> \mu + \sigma$	1.0334	(0.1324)	0.8965	(0.1126)	1.0114	(0.0587)	0.9511	(0.0550)
conscientiousness								
score $< \mu - \sigma$	0.9549	(0.1157)	0.9582	(0.1159)	0.9721	(0.0537)	0.9740	(0.0544)
score $> \mu + \sigma$	0.8978	(0.1107)	0.8818	(0.1075)	0.9437	(0.0539)	0.9376	(0.0536)
agreeableness								
score $< \mu - \sigma$	0.9721	(0.1162)	0.9283	(0.1100)	0.9870	(0.0545)	0.9651	(0.0535)
score $> \mu + \sigma$	0.9321	(0.1180)	0.9414	(0.1194)	0.9727	(0.0563)	0.9706	(0.0566)
local conditions at origin (district)								
GDP growth	1.0132*	(0.0080)			1.0066 *	(0.0037)		
unemployment growth	1.2131***	(0.0600)			1.0977 ***	(0.0267)		
population density (log)	0.8314***	(0.0427)			0.9207 ***	(0.0227)		
recreational area (per capita, log)	0.6009***	(0.0738)			0.7897 ***	(0.0458)		
constant					✓		✓	
cut points ($\kappa_1, \kappa_2, \kappa_3$)	✓		✓					
observations	1717		1717		1717		1717	
log likelihood	-2085.34		-2124.15		-2242.81		-2293.17	
df	28		24		28		24	
LR χ^2 (df)	133.20		61.83		125.36		60.34	
prob > χ^2	0.0000		0.0000		0.0000		0.0001	
pseudo R-squared	0.0320		0.0139					
Brant test (χ^2 / df / P>χ^2)	66.64 / 56 / 0.156		58.00 / 48 / 0.153					
Wolfe-Gould test (χ^2 / df / P>χ^2)	73.27 / 56 / 0.061		55.09 / 48 / 0.224					

*** p<0.01, ** p<0.05, * p<0.1

Table A3.5: Model comparison – binary scope approach

dependent variable	b_{i,C_0}										b^L_{i,C_0}					
estimation method	logit										logit					
	OR	s.e.	OR	s.e.	OR	s.e.	OR	s.e.	OR	s.e.	OR	s.e.	OR	s.e.	OR	s.e.
gender (female)	1.2546	(0.1744)	1.2638*	(0.1742)	1.1234	(0.1518)	1.1032	(0.1364)	1.0969	(0.1348)	1.2537	(0.1732)	1.2619*	(0.1728)	1.1086	(0.1364)
age	0.8309***	(0.0412)	0.8363***	(0.0415)	0.8673***	(0.0405)	0.8697***	(0.0402)	0.8793***	(0.0407)	0.8326***	(0.0410)	0.8383***	(0.0413)	0.8714***	(0.0401)
academic household	1.2383	(0.1614)	1.2504*	(0.1633)	1.2180	(0.1538)	1.2082	(0.1511)	1.2233	(0.1513)	1.1904	(0.1540)	1.2039	(0.1560)	1.1670	(0.1450)
uec grade	0.7850**	(0.0967)	0.8107*	(0.0996)	0.6982***	(0.0837)	0.7091***	(0.0822)	0.6868***	(0.0784)	0.7802**	(0.0956)	0.8068*	(0.0987)	0.7047***	(0.0813)
vocational training	1.4483	(0.3559)	1.4215	(0.3456)	1.4218	(0.3276)	1.4016	(0.3168)	1.3656	(0.3077)	1.4599	(0.3573)	1.4287	(0.3458)	1.4123	(0.3185)
partnership																
< 6 months	1.3020	(0.3523)	1.3168	(0.3528)	1.2757	(0.3390)	1.3049	(0.3427)	1.3738	(0.3613)	1.3329	(0.3593)	1.3461	(0.3592)	1.3299	(0.3487)
6-12 months	0.8147	(0.1805)	0.8389	(0.1849)	0.7600	(0.1644)	0.7574	(0.1648)	0.7688	(0.1633)	0.8279	(0.1829)	0.8525	(0.1876)	0.7714	(0.1674)
1-2 years	0.7231	(0.1534)	0.7189	(0.1519)	0.6868*	(0.1405)	0.6972*	(0.1416)	0.7045*	(0.1409)	0.7123	(0.1505)	0.7063*	(0.1485)	0.6862*	(0.1385)
2-3 years	1.0540	(0.2370)	1.0297	(0.2305)	1.0246	(0.2277)	1.0187	(0.2247)	0.9911	(0.2176)	1.0667	(0.2390)	1.0423	(0.2325)	1.0326	(0.2274)
> 3 years	1.1600	(0.2926)	1.1522	(0.2830)	1.1051	(0.2644)	1.1218	(0.2672)	1.1384	(0.2711)	1.1694	(0.2937)	1.1609	(0.2841)	1.1321	(0.2695)
risk attitude (career domain)																
score $< \mu - \sigma$	1.0470	(0.2023)	1.0243	(0.1958)	1.0851	(0.2110)	1.0403	(0.1984)			1.0534	(0.2033)	1.0316	(0.1970)	1.0484	(0.1998)
score $> \mu + \sigma$	0.7992	(0.1234)	0.7919	(0.1205)	0.8238	(0.1198)	0.8400	(0.1209)			0.7799	(0.1198)	0.7753*	(0.1173)	0.8235	(0.1179)
patience																
score $< \mu - \sigma$	0.5446***	(0.0840)	0.5518***	(0.0843)	0.5734***	(0.0856)	0.5760***	(0.0853)			0.5607***	(0.0862)	0.5680***	(0.0866)	0.5887***	(0.0870)
score $> \mu + \sigma$	1.3354	(0.2545)	1.3669*	(0.2553)	1.3375	(0.2430)	1.2831	(0.2250)			1.3541	(0.2567)	1.3911*	(0.2586)	1.3149	(0.2302)
extraversion																
score $< \mu - \sigma$	0.8090	(0.1495)	0.7227*	(0.1290)	0.6874**	(0.1209)					0.8227	(0.1515)	0.7342*	(0.1307)		
score $> \mu + \sigma$	0.9754	(0.1555)	1.0154	(0.1599)	1.0006	(0.1552)					0.9718	(0.1539)	1.0135	(0.1586)		
neuroticism																
score $< \mu - \sigma$	0.8207	(0.1632)	0.8722	(0.1710)	0.8820	(0.1664)					0.8418	(0.1668)	0.8964	(0.1751)		
score $> \mu + \sigma$	0.8479	(0.1504)	0.8234	(0.1457)	0.8746	(0.1501)					0.8590	(0.1519)	0.8348	(0.1472)		
openness																
score $< \mu - \sigma$	0.9319	(0.1479)	0.9167	(0.1446)	0.9455	(0.1478)					0.9259	(0.1463)	0.9108	(0.1430)		
score $> \mu + \sigma$	0.9775	(0.1669)	0.9942	(0.1688)	0.8498	(0.1372)					0.9609	(0.1630)	0.9801	(0.1654)		
conscientiousness																
score $< \mu - \sigma$	1.0069	(0.1588)	0.9812	(0.1543)	0.9827	(0.1523)					0.9628	(0.1504)	0.9396	(0.1463)		
score $> \mu + \sigma$	0.9119	(0.1589)	0.9238	(0.1592)	0.8945	(0.1504)					0.9114	(0.1584)	0.9254	(0.1591)		
agreeableness																
score $< \mu - \sigma$	1.0108	(0.1584)	0.9835	(0.1543)	0.9151	(0.1406)					1.0251	(0.1601)	0.9990	(0.1562)		
score $> \mu + \sigma$	1.0808	(0.1866)	1.1040	(0.1900)	1.0903	(0.1858)					1.0738	(0.1843)	1.0969	(0.1876)		
importance of proximity (family)																
score $< \mu - \sigma$	0.8692	(0.1356)									0.8969	(0.1395)				
score $> \mu + \sigma$	1.0320	(0.1874)									1.0480	(0.1894)				
adaptability																
score $< \mu - \sigma$	0.6333***	(0.0958)									0.6337***	(0.0955)				
score $> \mu + \sigma$	1.1099	(0.2207)									1.1196	(0.2217)				
local conditions at origin (district)																
GDP growth	1.0183*	(0.0102)	1.0192*	(0.0102)							1.0180*	(0.0101)	1.0189*	(0.0101)		
unemployment growth	1.1445**	(0.0766)	1.1366*	(0.0755)							1.1356*	(0.0755)	1.1274*	(0.0745)		
population density (log)	0.7883***	(0.0527)	0.7887***	(0.0526)							0.7862***	(0.0524)	0.7866***	(0.0522)		
recreational area (per capita, log)	0.4605***	(0.0778)	0.4685***	(0.0788)							0.4607***	(0.0777)	0.4680***	(0.0785)		
constant	✓		✓		✓		✓		✓		✓		✓		✓	
observations	1717		1717		1717		1717		1717		1717		1717		1717	
log likelihood	-828.90		-833.96		-866.50		-870.83		-880.77		-835.30		-840.34		-876.22	
df	32		28		24		14		10		32		28		14	
LR χ^2 (df)	127.39		117.21		69.68		59.85		38.47		126.20		116.03		59.44	
prob > χ^2	0.0000		0.0000		0.0000		0.0000		0.0000		0.0000		0.0000		0.0000	
pseudo R-squared	0.0802		0.0746		0.0385		0.0337		0.0227		0.0783		0.0728		0.0332	

*** p<0.01, ** p<0.05, * p<0.1

Note: Robust standard errors have been implemented.

Table A3.6: Model comparison – influential factors for the initial choice set's components (various models)

dependent variable		d^{avg}_{i,C_0}										d^{min}_{i,C_0}		d^{max}_{i,C_0}		r^{acg}_{d,i,C_0}	
estimation method		Γ, log-link										Γ, log-link		Γ, log-link		Γ, log-link	
		coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.
gender (female)		0.0188	(0.0489)	0.0090	(0.0491)	-0.0172	(0.0486)	0.0019	(0.0468)	-0.0044	(0.0470)	0.0201	(0.0844)	-0.0264	(0.0475)	-0.0520	(0.0565)
age		0.0301*	(0.0177)	0.0366**	(0.0178)	0.0416 **	(0.0179)	0.0427 **	(0.0181)	0.0508 ***	(0.0180)	0.0956 ***	(0.0303)	0.0173	(0.0173)	0.0380 *	(0.0208)
academic household		0.1832***	(0.0458)	0.2080***	(0.0465)	0.2023 ***	(0.0462)	0.1961 ***	(0.0459)	0.2036 ***	(0.0459)	0.1617 **	(0.0819)	0.2170 ***	(0.0440)	0.2154 ***	(0.0530)
uec grade		-0.0637	(0.0419)	-0.0428	(0.0427)	-0.0516	(0.0421)	-0.0464	(0.0401)	-0.0617	(0.0399)	0.0334	(0.0751)	-0.0865 **	(0.0398)	-0.1047 **	(0.0488)
vocational training		-0.0770	(0.0878)	-0.1312	(0.0873)	-0.1398	(0.0869)	-0.1499 *	(0.0878)	-0.1600 *	(0.0870)	-0.3038 **	(0.1465)	-0.0494	(0.0848)	-0.2001 **	(0.1008)
partnership	< 6 months	0.0099	(0.0867)	-0.0067	(0.0872)	-0.0095	(0.0852)	-0.0100	(0.0845)	0.0031	(0.0828)	0.0885	(0.1364)	-0.0092	(0.0810)	-0.0279	(0.0962)
	6-12 months	-0.1505*	(0.0889)	-0.1788**	(0.0907)	-0.1925 **	(0.0915)	-0.2105 **	(0.0914)	-0.2216 **	(0.0899)	-0.2674 *	(0.1559)	-0.1653 *	(0.0906)	-0.1831 *	(0.1092)
	1-2 years	-0.1440*	(0.0822)	-0.2233***	(0.0818)	-0.2207 ***	(0.0808)	-0.2194 ***	(0.0809)	-0.2148 ***	(0.0820)	-0.0439	(0.1350)	-0.2391 ***	(0.0774)	-0.2496 ***	(0.0942)
	2-3 years	-0.1520*	(0.0822)	-0.2029**	(0.0833)	-0.1806 **	(0.0866)	-0.1647 *	(0.0889)	-0.1900 **	(0.0865)	-0.1808	(0.1521)	-0.1717 **	(0.0799)	-0.2631 ***	(0.0977)
	> 3 years	-0.3600***	(0.0962)	-0.3940***	(0.0996)	-0.3649 ***	(0.1000)	-0.3633 ***	(0.1010)	-0.3512 ***	(0.1030)	-0.3488 **	(0.1643)	-0.3478 ***	(0.0994)	-0.3829 ***	(0.1172)
risk attitude	score $< \mu - \sigma$	-0.1433*	(0.0738)	-0.1581**	(0.0756)	-0.1471 *	(0.0751)	-0.1769 **	(0.0745)			-0.2810 **	(0.1294)	-0.0833	(0.0709)	-0.1318	(0.0876)
(career domain)	score $> \mu + \sigma$	0.0095	(0.0543)	0.0408	(0.0539)	0.0465	(0.0540)	0.0554	(0.0542)			0.1099	(0.0971)	0.0586	(0.0510)	0.0494	(0.0627)
patience	score $< \mu - \sigma$	-0.1913***	(0.0643)	-0.1861***	(0.0664)	-0.1774 ***	(0.0666)	-0.1700 **	(0.0674)			0.0303	(0.1093)	-0.2394 ***	(0.0632)	-0.1812 **	(0.0773)
	score $> \mu + \sigma$	0.1177*	(0.0624)	0.1711***	(0.0630)	0.1451 **	(0.0621)	0.1414 **	(0.0612)			0.1485	(0.1069)	0.1384 **	(0.0582)	0.1784 **	(0.0696)
extraversion	score $< \mu - \sigma$	-0.1543**	(0.0777)	-0.2344***	(0.0761)	-0.2455 ***	(0.0764)					-0.2658 **	(0.1319)	-0.2355 ***	(0.0734)	-0.2470 ***	(0.0901)
	score $> \mu + \sigma$	-0.0437	(0.0578)	0.0232	(0.0595)	0.0130	(0.0593)					0.0624	(0.1006)	0.0006	(0.0550)	0.0040	(0.0672)
neuroticism	score $< \mu - \sigma$	-0.0136	(0.0714)	0.0253	(0.0725)	0.0208	(0.0726)					0.0494	(0.1264)	-0.0020	(0.0674)	0.0039	(0.0833)
	score $> \mu + \sigma$	0.0757	(0.0637)	0.0573	(0.0656)	0.0665	(0.0664)					0.1111	(0.1126)	0.0464	(0.0634)	0.0826	(0.0773)
openness	score $< \mu - \sigma$	-0.0910	(0.0573)	-0.1251**	(0.0567)	-0.1129 **	(0.0564)					-0.2042 **	(0.0964)	-0.0979 *	(0.0570)	-0.1490 **	(0.0654)
	score $> \mu + \sigma$	0.0894	(0.0600)	0.1164*	(0.0617)	0.0893	(0.0619)					0.0720	(0.1036)	0.0986 *	(0.0590)	0.0692	(0.0722)
conscientiousness	score $< \mu - \sigma$	0.0003	(0.0564)	0.0077	(0.0578)	0.0092	(0.0580)					-0.0471	(0.0997)	0.0225	(0.0565)	-0.0027	(0.0674)
	score $> \mu + \sigma$	-0.0892	(0.0630)	-0.0987	(0.0625)	-0.1005	(0.0621)					-0.2240 **	(0.1088)	-0.0831	(0.0593)	-0.1249 *	(0.0709)
agreeableness	score $< \mu - \sigma$	-0.0617	(0.0588)	-0.0558	(0.0595)	-0.0663	(0.0592)					-0.1201	(0.1026)	-0.0454	(0.0572)	-0.0409	(0.0696)
	score $> \mu + \sigma$	-0.0523	(0.0603)	-0.0708	(0.0611)	-0.0595	(0.0619)					-0.1884 *	(0.1065)	-0.0112	(0.0596)	-0.0824	(0.0705)
importance of	score $< \mu - \sigma$	0.2080***	(0.0545)														
proximity (family)	score $> \mu + \sigma$	-0.1839***	(0.0656)														
adaptability	score $< \mu - \sigma$	-0.1162*	(0.0614)														
	score $> \mu + \sigma$	0.2500***	(0.0660)														
local conditions at origin (district)																	
	GDP growth	0.0081**	(0.0032)	0.0079**	(0.0032)												
	unemployment growth	0.0287	(0.0230)	0.0227	(0.0233)												
	population density (log)	-0.0730***	(0.0253)	-0.0754***	(0.0255)												
	recreational area (per capita, log)	-0.2327***	(0.0658)	-0.2477***	(0.0663)												
constant		✓		✓		✓		✓		✓		✓		✓		✓	
observations		1714		1714		1714		1714		1714		1714		1714		1714	
log likelihood		-9530.70		-9554.65		-9568.16		-9578.51		-9589.02		-8078.01		-10459.99		-7233.39	
deviance		1208.03		1242.92		1240.93		1253.61		1268.05		1549.73		1236.63		2283.23	
rank (k)		33		29		25		15		11		25		25		25	
AIC		11.1595		11.1828		11.1939		11.1943		11.2019		9.4551		12. 2345		8.4695	
BIC		-11309.68		-11304.58		-11336.36		-11398.13		-11413.48		-11027.55		-11340.65		-10294.05	
link test: $P > \lvert z \rvert$ (H_0: coeff.$\hat{y}^2 = 0$)		0.013		0.000		0.318		0.918		0.603		0.550		0.279		0.203	

*** p<0.01, ** p<0.05, * p<0.1

Note: Table contains raw coefficients from GLM estimation (Gamma with log-link), applying robust standard errors. The dependent variable in the first five specifications is the 'average excess distance' measure in the application set. Columns 6 and 7 contain results for the dependent variables 'minimum excess distance' and 'maximum excess distance' measure. This measure for potential excess mobility is derived as difference between the geographic distance from previous location to a stated study place and the distance to the closest hypothetical alternative, given by the nearest university (of applied sciences) offering an economics programme. The dependent variable in column 8 is the average distance rank of the universities in the application set amongst all hypothetical alternatives, based on the full set of university (of applied sciences) offering an economics programme. Link test (Pregibon, 1979) is based on a second order approximation of the outcome variable, based on a model refit with the regressors $\hat{y}$ and $\hat{y}^2$. Under the Null (appropriate link-function), the coefficient estimate for $\hat{y}^2$ should be insignificant.

Table A3.7: Observed mobility – accounting for most preferred alternatives (OLS and IV)

dependent variable	$u_i \vert n^*_{i,C_1} = 2$		$u_i \vert n^*_{i,C_1} = 2$				$u_i \vert n^*_{i,C_1} \in [2{,}4]$			
estimation method	OLS		OLS		IV (2nd stage)		OLS		IV (2nd stage)	
	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.
gender (female)	-0.0006	(0.0325)	-0.0033	(0.0328)	-0.0115	(0.0597)	0.0743**	(0.0345)	0.0480	(0.0731)
age	-0.0130	(0.0116)	-0.0145	(0.0118)	-0.0316	(0.0205)	-0.0039	(0.0130)	-0.0318	(0.0261)
academic household	-0.0088	(0.0300)	-0.0092	(0.0301)	-0.0236	(0.0417)	0.0480	(0.0321)	0.0296	(0.0535)
uec grade	0.1269***	(0.0294)	0.1239***	(0.0293)	0.0808	(0.0509)	0.0477	(0.0317)	-0.0110	(0.0584)
vocational training	-0.0764	(0.0542)	-0.0720	(0.0546)	-0.0000	(0.0940)	-0.0798	(0.0610)	0.0226	(0.1152)
partnership										
< 6 months	-0.0140	(0.0558)	-0.0196	(0.0558)	-0.0632	(0.0862)	-0.0830	(0.0591)	-0.1628	(0.1056)
6-12 months	-0.0233	(0.0529)	-0.0276	(0.0533)	-0.0606	(0.0792)	-0.0936	(0.0582)	-0.1535	(0.1026)
1-2 years	-0.0733	(0.0508)	-0.0737	(0.0506)	-0.0467	(0.0893)	-0.0608	(0.0560)	-0.0334	(0.1093)
2-3 years	-0.0668	(0.0523)	-0.0654	(0.0525)	-0.0280	(0.0815)	-0.0807	(0.0585)	-0.0330	(0.1008)
> 3 years	0.0710	(0.0614)	0.0706	(0.0614)	0.0750	(0.0716)	0.0745	(0.0606)	0.0762	(0.0843)
risk attitude (career domain)										
score $< \mu - \sigma$	-0.0631	(0.0458)	-0.0605	(0.0458)	-0.0282	(0.0622)	-0.0778	(0.0498)	-0.0266	(0.0807)
score $> \mu + \sigma$	0.0309	(0.0359)	0.0295	(0.0362)	-0.0102	(0.0685)	0.0445	(0.0381)	-0.0067	(0.0847)
patience										
score $< \mu - \sigma$	0.0233	(0.0439)	0.0244	(0.0438)	0.0461	(0.0542)	-0.0601	(0.0456)	-0.0272	(0.0674)
score $> \mu + \sigma$	0.0191	(0.0390)	0.0157	(0.0389)	-0.0360	(0.0650)	0.0402	(0.0430)	-0.0335	(0.0754)
extraversion										
score $< \mu - \sigma$	-0.1006**	(0.0431)	-0.0892**	(0.0435)	0.0719	(0.1466)	-0.0643	(0.0509)	0.1772	(0.1800)
score $> \mu + \sigma$	0.0036	(0.0383)	-0.0069	(0.0390)	-0.1321	(0.1165)	0.0266	(0.0406)	-0.1759	(0.1420)
neuroticism										
score $< \mu - \sigma$	-0.0306	(0.0468)	-0.0423	(0.0468)	-0.1660	(0.1215)	-0.0052	(0.0495)	-0.2114	(0.1487)
score $> \mu + \sigma$	-0.0003	(0.0417)	0.0073	(0.0418)	0.1055	(0.0928)	-0.0372	(0.0449)	0.1181	(0.1188)
openness										
score $< \mu - \sigma$	-0.0307	(0.0372)	-0.0318	(0.0372)	-0.0306	(0.0499)	0.0458	(0.0400)	0.0394	(0.0634)
score $> \mu + \sigma$	0.0282	(0.0404)	0.0258	(0.0403)	-0.0098	(0.0561)	0.0434	(0.0422)	-0.0105	(0.0685)
conscientiousness										
score $< \mu - \sigma$	0.0153	(0.0401)	0.0178	(0.0401)	0.0494	(0.0538)	0.0056	(0.0413)	0.0530	(0.0636)
score $> \mu + \sigma$	0.0102	(0.0393)	0.0056	(0.0393)	-0.0447	(0.0618)	0.0073	(0.0427)	-0.0779	(0.0802)
agreeableness										
score $< \mu - \sigma$	-0.0841**	(0.0358)	-0.0805**	(0.0359)	-0.0495	(0.0579)	-0.0056	(0.0407)	0.0484	(0.0742)
score $> \mu + \sigma$	0.0859**	(0.0430)	0.0816*	(0.0426)	0.0340	(0.0606)	0.0789*	(0.0429)	0.0013	(0.0702)
x_1^{endog}: imp. of prox. (family)			0.0096	(0.0098)	0.0556	(0.1400)	0.0028	(0.0102)	0.1121	(0.1732)
x_2^{endog}: adaptability			0.0179*	(0.0109)	0.2350	(0.1810)	0.0060	(0.0119)	0.3508	(0.2179)
distance to closest alternative	✓		✓		✓					
constant	✓		✓		✓		✓		✓	
observations	1053		1053		1053		1053		1053	
df	25		27		27		27		27	
F / Wald χ^2	2.31		2.25		45.00		1.39		22.36	
prob > χ^2/ prob > F	0.0003		0.0003		0.0162		0.0907		0.7187	
adjusted R-squared	0.0262		0.0273				0.0088			
exogeneity test										
Wooldridge (1995) score test					2.00 (p=0.3673)				4.67 (p=0.0967)	
Regression based test					0.98 (p=0.3774)				2.29 (p=0.1017)	
1st stage: x_1^{endog}										
F(model)					4.94 (p=0.0000)				4.64 (p=0.0240)	
z_1: res. move during school					-0.3283 **	(0.1293)			-0.3342 **	(0.1293)
z_2: exchange participation					-0.0491	(0.1007)			-0.0788	(0.1011)
F(instruments)					3.41 (p=0.0333)				3.74 (p=0.0240)	
1st stage: x_2^{endog}										
F(model)					9.91 (p=0.0000)				9.92 (p=0.0000)	
z_1: res. move during school					0.0370	(0.1125)			0.0362	(0.1124)
z_2: exchange participation					0.2089 **	(0.0893)			0.2195 **	(0.0886)
F(instruments)					2.81 (p=0.0607)				3.14 (p=0.0434)	
weak instrument test										
F^{crit} $(\alpha = 0.10)$					7.03				7.03	
F^{crit} $(\alpha = 0.15)$					4.58				4.58	
F^{crit} $(\alpha = 0.20)$					3.95				3.95	

*** p<0.01, ** p<0.05, * p<0.1

Note: The dependent variable $u_i|n^*_{i,C_1} = 2$ is coded as one when the eventually selected location is not the closer alternative in comparison to the most preferred alternative. $u_i|n^*_{i,C_1} \in [2{,}4]$ is coded as one when the finally chosen location is not the closest alternative compared to all stated available alternatives. The two potentially endogenous variables (importance of proximity to family and adaptability to new circumstance) enter the specifications as quasi continuous variables (on a scale from 1 to 7). This modification is implemented with regard to the first stage estimations. F^{crit}report the critical values of Stock and Yogo's (2005) weak instrument test, assuming i.i.d. error structure.

Table A3.8: Model comparison – observed mobility (logit and ordered logit)

dependent variable		$u_i \mid n^*_{i,C_1} = 2$				$u_i \mid n^{L*}_{i,C_1} = 2$				$u_i \mid n^*_{i,C_1} \in [2,4]$				$r_u \mid n^*_{i,C_1} \in [2,4]$			
estimation method		logit				logit				logit				ologit			
		OR	s.e.	OR	s.e.	OR	s.e.	OR	s.e.	OR	s.e.	OR	s.e.	OR	s.e.	OR	s.e.
gender (female)		0.9144	(0.1410)	1.1203	(0.1547)	0.8985	(0.1368)	1.0599	(0.1440)	1.2708 *	(0.1840)	1.3782 **	(0.1804)	1.2445	(0.1687)	1.3087 **	(0.1610)
age		0.9173	(0.0556)	0.9451	(0.0550)	0.9135	(0.0533)	0.9409	(0.0528)	0.9784	(0.0541)	0.9926	(0.0525)	0.9650	(0.0502)	0.9886	(0.0494)
academic household		0.9099	(0.1278)	0.9338	(0.1271)	0.9307	(0.1286)	0.9514	(0.1273)	1.1900	(0.1588)	1.2071	(0.1555)	1.0382	(0.1308)	1.0730	(0.1289)
uec grade		1.8684***	(0.2774)	1.8190***	(0.2385)	1.7210 ***	(0.2488)	1.6822 ***	(0.2157)	1.1942	(0.1619)	1.2248 *	(0.1505)	1.3721 **	(0.1748)	1.4016 ***	(0.1651)
vocational training		0.7881	(0.2163)	0.6681	(0.1767)	0.8259	(0.2204)	0.7041	(0.1820)	0.7664	(0.1947)	0.6987	(0.1739)	0.6809 *	(0.1557)	0.6049 **	(0.1362)
partnership	< 6 months	0.8988	(0.2337)	0.9719	(0.2460)	0.8589	(0.2211)	0.9245	(0.2313)	0.6984	(0.1756)	0.7493	(0.1759)	0.7626	(0.1864)	0.7868	(0.1796)
	6-12 months	0.8153	(0.2122)	0.8531	(0.2166)	0.7711	(0.1973)	0.8179	(0.2051)	0.6307 *	(0.1527)	0.6876	(0.1629)	0.6263 **	(0.1420)	0.6895 *	(0.1530)
	1-2 years	0.6801	(0.1740)	0.7081	(0.1752)	0.8567	(0.2093)	0.8817	(0.2082)	0.7450	(0.1688)	0.7940	(0.1778)	0.8516	(0.1923)	0.8904	(0.2018)
	2-3 years	0.7361	(0.1953)	0.7306	(0.1869)	0.6684	(0.1755)	0.6714	(0.1703)	0.7124	(0.1727)	0.7267	(0.1702)	0.7069	(0.1593)	0.7137	(0.1553)
	> 3 years	1.3892	(0.3904)	1.3462	(0.3571)	1.4958	(0.4056)	1.4458	(0.3771)	1.3726	(0.3504)	1.3396	(0.3444)	1.3960	(0.3239)	1.3364	(0.3047)
risk attitude	score $< \mu - \sigma$	0.7371	(0.1719)	0.7123	(0.1615)	0.6840 *	(0.1557)	0.6653 *	(0.1475)	0.7020 *	(0.1449)	0.7232	(0.1464)	0.6957 *	(0.1330)	0.6881 *	(0.1315)
(career domain)	score $> \mu + \sigma$	1.1391	(0.1859)	1.1614	(0.1855)	1.1060	(0.1779)	1.1457	(0.1801)	1.1792	(0.1876)	1.2275	(0.1895)	1.0647	(0.1507)	1.1379	(0.1558)
patience	score $< \mu - \sigma$	1.0818	(0.2169)	1.0963	(0.2092)	0.9856	(0.1940)	1.0071	(0.1901)	0.7622	(0.1448)	0.7858	(0.1429)	0.7849	(0.1479)	0.8174	(0.1487)
	score $> \mu + \sigma$	0.9517	(0.1778)	1.0613	(0.1911)	0.9982	(0.1835)	1.0973	(0.1932)	1.1130	(0.2024)	1.2071	(0.2083)	1.0603	(0.1711)	1.1448	(0.1742)
extraversion	score $< \mu - \sigma$	0.6140**	(0.1439)			0.5890 **	(0.1367)			0.7424	(0.1559)			0.7463	(0.1458)		
	score $> \mu + \sigma$	0.9006	(0.1593)			0.9561	(0.1656)			1.0682	(0.1787)			1.0777	(0.1671)		
neuroticism	score $< \mu - \sigma$	0.7969	(0.1780)			0.8600	(0.1854)			0.9591	(0.1965)			0.9523	(0.1912)		
	score $> \mu + \sigma$	1.0524	(0.2071)			0.9671	(0.1882)			0.8589	(0.1593)			0.7586 *	(0.1197)		
openness	score $< \mu - \sigma$	0.8410	(0.1573)			0.8803	(0.1583)			1.1779	(0.1979)			1.1085	(0.1722)		
	score $> \mu + \sigma$	1.0568	(0.1933)			1.0485	(0.1909)			1.1020	(0.1928)			1.0336	(0.1663)		
conscientiousness	score $< \mu - \sigma$	1.0811	(0.2004)			1.0336	(0.1871)			1.0335	(0.1779)			0.9989	(0.1654)		
	score $> \mu + \sigma$	1.0546	(0.1990)			0.9973	(0.1840)			1.0251	(0.1806)			0.8886	(0.1355)		
agreeableness	score $< \mu - \sigma$	0.6450**	(0.1204)			0.6560 **	(0.1190)			0.9610	(0.1596)			0.9658	(0.1495)		
	score $> \mu + \sigma$	1.4637**	(0.2665)			1.4282 **	(0.2568)			1.4111 *	(0.2528)			1.4061 **	(0.2322)		
importance of	score $< \mu - \sigma$	0.8744	(0.1532)			0.9235	(0.1587)			0.9700	(0.1571)			0.9838	(0.1505)		
proximity (family)	score $> \mu + \sigma$	1.4003*	(0.2809)			1.4540 *	(0.2893)			1.4444 *	(0.2837)			1.4124 **	(0.2399)		
adaptability	score $< \mu - \sigma$	0.9073	(0.1723)			0.8962	(0.1663)			1.0052	(0.1724)			0.9315	(0.1456)		
	score $> \mu + \sigma$	1.7249***	(0.3499)			1.6290 **	(0.3244)			1.3779	(0.2808)			1.4545 **	(0.2754)		
local conditions at origin (district)																	
	GDP growth	0.9753**	(0.0117)			0.9745 **	(0.0116)			0.9796 *	(0.0104)			0.9746 **	(0.0100)		
	unemployment growth	0.8318**	(0.0673)			0.8393 **	(0.0672)			0.8171 ***	(0.0637)			0.8209 ***	(0.0585)		
	population density (log)	1.1328	(0.0934)			1.1019	(0.0890)			1.0103	(0.0773)			1.0136	(0.0730)		
	recreational area (per capita, log)	0.8364	(0.1636)			0.8054	(0.1558)			0.8496	(0.1635)			0.7791	(0.1439)		
distance to closest alternative		✓		✓		✓		✓		✓		✓		✓		✓	
constant		✓		✓		✓		✓		✓		✓					
cut points (κ_1, κ_2)														✓		✓	
observations		1053		1053		1053		1053		1053		1053		1053		1053	
log likelihood		-636.06		-659.04		-653.58		-675.86		-701.83		-715.45		-1066.19		-1084.59	
df		33		15		33		15		33		15		33		15	
LR χ^2 (df)		72.84		30.41		69.18		26.93		49.15		24.48		66.07		28.21	
prob > χ^2		0.0001		0.0105		0.0002		0.0294		0.0349		0.0573		0.0005		0.0203	
pseudo R-squared		0.0586		0.0246		0.0539		0.0217		0.0365		0.0178		0.0306		0.0138	
Brant test (χ^2 / df / P>χ^2)														50.96 / 33 / 0.024		32.72 / 15 / 0.005	
Wolfe-Gould test (χ^2 / df / P>χ^2)														45.66 / 33 / 0.070		28.23 / 15 / 0.020	

*** p<0.01, ** p<0.05, * p<0.1

Note: Robust standard errors implemented. The pseudo R-squared is calculated as $R^2 = 1 - \frac{L(model\ df)}{L(df=1)}$.

Table A3.9: Partial proportional odds model – ranked observed mobility

dependent variable		$r_u\|n^*_{i,C_1} \in [2,4]$											
estimation method		partial proportional odds model (generalised ordered logit model)											
		intermediate and maximum vs minimum distance		maximum vs. minimum and intermediate distance		intermediate and maximum vs minimum distance		maximum vs. minimum and intermediate distance		intermediate and maximum vs minimum distance		maximum vs. minimum and intermediate distance	
		OR	s.e.	OR	s.e.	OR	s.e.	OR	s.e.	OR	s.e.	OR	s.e.
gender (female)		1.2408	(0.1676)	1.2408	(0.1676)	1.3424 **	(0.1759)	1.3424 **	(0.1759)	1.3148 **	(0.1622)	1.3148 **	(0.1622)
age		0.9647	(0.0501)	0.9647	(0.0501)	0.9795	(0.0485)	0.9795	(0.0485)	0.9902	(0.0490)	0.9902	(0.0490)
academic household		**1.1709**	(0.1573)	**0.7641**	(0.1264)	**1.1994**	(0.1574)	**0.8099**	(0.1310)	**1.1995**	(0.1544)	**0.8310**	(0.1329)
uec grade		**1.2124**	(0.1635)	**1.8100*****	(0.2831)	**1.2394** *	(0.1607)	**1.8155** ***	(0.2796)	**1.2287** *	(0.1508)	**1.9076** ***	(0.2855)
vocational training		**0.7984**	(0.1937)	**0.4608****	(0.1390)	**0.7285**	(0.1734)	**0.4041** ***	(0.1197)	**0.7077**	(0.1678)	**0.3782** ***	(0.1126)
partnership	< 6 months	0.7627	(0.1873)	0.7627	(0.1873)	0.7742	(0.1817)	0.7742	(0.1817)	0.7887	(0.1805)	0.7887	(0.1805)
	6-12 months	0.6354**	(0.1431)	0.6354**	(0.1431)	0.6843 *	(0.1533)	0.6843 *	(0.1533)	0.6882 *	(0.1535)	0.6882 *	(0.1535)
	1-2 years	0.8718	(0.2017)	0.8718	(0.2017)	0.8897	(0.2088)	0.8897	(0.2088)	0.8940	(0.2035)	0.8940	(0.2035)
	2-3 years	0.7152	(0.1613)	0.7152	(0.1613)	0.7055	(0.1565)	0.7055	(0.1565)	0.7169	(0.1546)	0.7169	(0.1546)
	> 3 years	1.4208	(0.3422)	1.4208	(0.3422)	1.3960	(0.3275)	1.3960	(0.3275)	1.3526	(0.3169)	1.3526	(0.3169)
risk attitude	score $< \mu - \sigma$	0.7076*	(0.1376)	0.7076*	(0.1376)	0.7127 *	(0.1382)	0.7127 *	(0.1382)	0.6998 *	(0.1328)	0.6998 *	(0.1328)
(career domain)	score $> \mu + \sigma$	1.0656	(0.1508)	1.0656	(0.1508)	1.0976	(0.1533)	1.0976	(0.1533)	1.1300	(0.1548)	1.1300	(0.1548)
patience	score $< \mu - \sigma$	0.7934	(0.1452)	0.7934	(0.1452)	0.8170	(0.1487)	0.8170	(0.1487)	0.8233	(0.1482)	0.8233	(0.1482)
	score $> \mu + \sigma$	1.0698	(0.1760)	1.0698	(0.1760)	1.1515	(0.1845)	1.1515	(0.1845)	1.1333	(0.1733)	1.1333	(0.1733)
extraversion	score $< \mu - \sigma$	0.7543	(0.1507)	0.7543	(0.1507)	0.7569	(0.1471)	0.7569	(0.1471)				
	score $> \mu + \sigma$	1.0814	(0.1676)	1.0814	(0.1676)	1.1640	(0.1789)	1.1640	(0.1789)				
neuroticism	score $< \mu - \sigma$	0.9548	(0.1879)	0.9548	(0.1879)	1.0160	(0.1940)	1.0160	(0.1940)				
	score $> \mu + \sigma$	**0.8797**	(0.1596)	**0.4962*****	(0.1213)	**0.8579**	(0.1545)	**0.4785** ***	(0.1174)				
openness	score $< \mu - \sigma$	1.1225	(0.1748)	1.1225	(0.1748)	1.1338	(0.1726)	1.1338	(0.1726)				
	score $> \mu + \sigma$	1.0358	(0.1701)	1.0358	(0.1701)	1.1466	(0.1840)	1.1466	(0.1840)				
conscientiousness	score $< \mu - \sigma$	0.9911	(0.1575)	0.9911	(0.1575)	0.9701	(0.1526)	0.9701	(0.1526)				
	score $> \mu + \sigma$	**1.0052**	(0.1736)	**0.6547***	(0.1486)	**1.0145**	(0.1746)	**0.6688** *	(0.1507)				
agreeableness	score $< \mu - \sigma$	0.9591	(0.1481)	0.9591	(0.1481)	0.9790	(0.1494)	0.9790	(0.1494)				
	score $> \mu + \sigma$	1.4413**	(0.2416)	1.4413**	(0.2416)	1.4366 **	(0.2424)	1.4366 **	(0.2424)				
importance of	score $< \mu - \sigma$	0.9943	(0.1522)	0.9943	(0.1522)								
proximity (family)	score $> \mu + \sigma$	1.4038*	(0.2445)	1.4038*	(0.2445)								
adaptability	score $< \mu - \sigma$	0.9357	(0.1477)	0.9357	(0.1477)								
	score $> \mu + \sigma$	1.4401*	(0.2724)	1.4401*	(0.2724)								
local conditions at origin (district)													
	GDP growth	0.9739**	(0.0103)	0.9739**	(0.0103)								
	unemployment growth	0.8103***	(0.0586)	0.8103***	(0.0586)								
	population density (log)	1.0132	(0.0726)	1.0132	(0.0726)								
	recreational area (per capita, log)	**0.8672**	(0.1666)	**0.6200****	(0.1356)								
distance to closest alternative		✓				✓				✓			
constant		✓				✓				✓			
observations		1053				1053				-1073.30			
log likelihood		-1046.76				-1059.93				18			
df		39				30				49.50			
LR χ^2 (df)		101.03				72.97				0.0001			
prob > χ^2		0.0000				0.0000				0.0241			
pseudo R-squared		0.0482				0.0362				-1099.79			
proportional odds test (final model) (χ^2 / df / prob >χ^2)		11.97 / 27 / 0.9944				8.21 / 20 / 0.9904				6.78 / 12 / 0.8717			

*** p<0.01, ** p<0.05, * p<0.1

Note: Robust standard errors implemented. The pseudo R-squared is calculated as $R^2 = 1 - L(model\,df)/L(df = 1)$. Estimation based on `gologit2` (Williams, 2006), with partial proportional odds introduced for variables not violating the proportional odds assumption at a significance level of 5 %. Reported odds ratios in bold differ across the outcome levels; these are the cases where the proportional odds assumption has initially been violated. The proportional odds test for the final model refers to a test of parallel lines of those variables (H_0: partial proportional odds assumption holds), which have not been identified as causing the assumption's violation in the first place.

Table A3.10: Observed mobility – alternative distance concepts

dependent variable		$u_i \mid n^*_{i,C_1} = 2$											
estimation method		logit											
		road distance						travel time					
		OR	s.e.	OR	s.e.	OR	s.e.	OR	s.e.	OR	s.e.	OR	s.e.
gender (female)		0.9193	(0.1418)	1.0044	(0.1508)	1.1330	(0.1561)	0.9704	(0.1499)	1.0362	(0.1564)	1.1571	(0.1605)
age		0.9144	(0.0550)	0.9283	(0.0553)	0.9416	(0.0547)	0.9227	(0.0550)	0.9368	(0.0551)	0.9460	(0.0540)
academic household		0.9511	(0.1331)	0.9925	(0.1378)	0.9632	(0.1307)	0.9377	(0.1305)	0.9561	(0.1324)	0.9404	(0.1280)
uec grade		1.9287***	(0.2852)	1.8946***	(0.2703)	1.8614 ***	(0.2434)	1.9604 ***	(0.2900)	1.9421 ***	(0.2785)	1.9397 ***	(0.2564)
vocational training		0.7945	(0.2165)	0.7167	(0.1906)	0.6832	(0.1800)	0.9216	(0.2449)	0.8363	(0.2186)	0.7938	(0.2051)
partnership	< 6 months	0.8550	(0.2225)	0.8877	(0.2252)	0.9297	(0.2355)	0.8540	(0.2193)	0.8699	(0.2202)	0.9121	(0.2319)
	6-12 months	0.8145	(0.2088)	0.8812	(0.2222)	0.8574	(0.2155)	0.7656	(0.1968)	0.8000	(0.2021)	0.7671	(0.1929)
	1-2 years	0.6068*	(0.1561)	0.6286*	(0.1618)	0.6458 *	(0.1614)	0.4844 ***	(0.1270)	0.4986 ***	(0.1316)	0.5138 **	(0.1336)
	2-3 years	0.7368	(0.1923)	0.7355	(0.1863)	0.7486	(0.1885)	0.6072 *	(0.1614)	0.6178 *	(0.1605)	0.6269 *	(0.1617)
	> 3 years	1.1687	(0.3283)	1.1723	(0.3191)	1.1499	(0.3074)	0.9675	(0.2715)	0.9685	(0.2643)	0.9402	(0.2527)
risk attitude	score $< \mu - \sigma$	0.8514	(0.1940)	0.8506	(0.1906)	0.8238	(0.1816)	0.7985	(0.1822)	0.8239	(0.1854)	0.7997	(0.1765)
(career domain)	score $> \mu + \sigma$	1.1137	(0.1822)	1.1262	(0.1812)	1.1372	(0.1817)	1.1547	(0.1892)	1.1776	(0.1899)	1.1786	(0.1889)
patience	score $< \mu - \sigma$	1.0091	(0.2056)	1.0450	(0.2099)	1.0211	(0.1970)	0.8823	(0.1811)	0.9221	(0.1880)	0.9137	(0.1791)
	score $> \mu + \sigma$	1.0714	(0.1985)	1.2119	(0.2203)	1.1761	(0.2098)	1.1010	(0.2041)	1.2168	(0.2217)	1.1920	(0.2128)
extraversion	score $< \mu - \sigma$	0.5632**	(0.1347)	0.5575**	(0.1305)			0.5761 **	(0.1372)	0.5822 **	(0.1358)		
	score $> \mu + \sigma$	0.9702	(0.1705)	1.0779	(0.1851)			0.8845	(0.1562)	0.9466	(0.1633)		
neuroticism	score $< \mu - \sigma$	0.7353	(0.1656)	0.7906	(0.1760)			0.7807	(0.1749)	0.8373	(0.1852)		
	score $> \mu + \sigma$	1.0387	(0.2047)	0.9921	(0.1928)			1.0257	(0.2024)	1.0057	(0.1949)		
openness	score $< \mu - \sigma$	0.8437	(0.1567)	0.8684	(0.1552)			0.8976	(0.1639)	0.9313	(0.1655)		
	score $> \mu + \sigma$	1.1368	(0.2077)	1.2204	(0.2215)			1.1467	(0.2105)	1.2151	(0.2212)		
conscientiousness	score $< \mu - \sigma$	1.0487	(0.1940)	1.0336	(0.1864)			1.0717	(0.1998)	1.0546	(0.1925)		
	score $> \mu + \sigma$	1.0244	(0.1920)	1.0285	(0.1914)			0.9778	(0.1831)	1.0008	(0.1859)		
agreeableness	score $< \mu - \sigma$	0.6931**	(0.1281)	0.6994*	(0.1284)			0.8133	(0.1484)	0.8125	(0.1476)		
	score $> \mu + \sigma$	1.4190*	(0.2585)	1.4184*	(0.2585)			1.5940 **	(0.2927)	1.5919 **	(0.2908)		
importance of	score $< \mu - \sigma$	0.8977	(0.1554)					0.9404	(0.1627)				
proximity (family)	score $> \mu + \sigma$	1.4775*	(0.2969)					1.5567 **	(0.3127)				
adaptability	score $< \mu - \sigma$	0.8844	(0.1675)					0.9785	(0.1843)				
	score $> \mu + \sigma$	1.5501**	(0.3153)					1.4476 *	(0.2944)				
local conditions at origin (district)													
	GDP growth	0.9762**	(0.0116)					0.9764 **	(0.0115)				
	unemployment growth	0.8489**	(0.0681)					0.9183	(0.0751)				
	population density (log)	1.1167	(0.0915)					1.0176	(0.0838)				
	recreational area (per capita, log)	0.8579	(0.1679)					0.8565	(0.1685)				
distance to closest alternative			✓				✓				✓		
constant			✓				✓				✓		
observations		1053		1053		1053		1053		1053		1053	
log likelihood		-639.58		-650.42		-661.32		-641.73		-648.94		-658.35	
df		33		25		15		33		25		15	
LR χ^2(df)		69.07		47.79		30.57		65.48		51.90		37.51	
prob > χ^2		0.0002		0.0039		0.0100		0.0006		0.0012		0.0011	
pseudo R2		0.0561		0.0401		0.0240		0.0547		0.0441		0.0303	

*** p<0.01, ** p<0.05, * p<0.1

Note: Robust standard errors implemented. The pseudo R-squared is calculated as $R^2 = 1 - \frac{L(model\ df)}{L(df=1)}$.

Table A4.1: Construction and distributional properties of simulated explanatory variables and error components

simulated variable	underlying distribution	Stata syntax	properties

gender (1=female)	Uniform $U(0,1)$	`gen g_base=runiform(0,1)`
		`gen g=1 if g_base>=0.5`
		`replace g=0 if g_base<0.5`
			$E[g_i] = 0.5$

age	Gamma $\Gamma(2,1.5)$	`gen a=round(17+rgamma(2,1.5))`	$E[a_i] = 20$, $\min[a_i] = 17$

university entrance certificate grade	Normal $N(2.4,0.6)$	`gen c_base=round(rnormal(2.4,0.6),0.1)`
		`gen c=c_base`
		`replace c=1.0 if c<1.0`
		`replace c=4.0 if c>4.0`
			$E[c_i] \approx 2.4$,
			$\min[c_i] = 1.0$,
			$\max[c_i] = 4.0$

risk	Normal $N(0,1)$	`gen r_base=rnormal(0,1)`
		`gen r=r_base+g_base/2 if g==0`
		`replace r=r_base-g_base/2 if g==1`
			$E[r_i] \approx -0.125$,
			$\rho[r_i, g_i] < 0$

number of alternative applications	Neg. binomial $NB(3,0.5)$	`gen n_base=rnbinomial(3,0.5)`
		`gen n=round(n_base-r,1)`
		`replace n=1 if n<1`
			$E[n_i] \approx 3$
			$\rho[n_i, r_i] < 0$

clustered error component	$v_i \sim i.i.d. U(-0.5,0.5)$	`gen e_cc=runiform(-0.5,0.5)`	$E[v_i] = 0$
type 1 extreme value error	$u_{il} \sim i.i.d.$ $Gumbel(0,1)$	`gen e_t1=-ln(-ln(runiform(0,1))`	$E[u_{il}] = \gamma^{Euler} =$ 0.5772
normally distributed error	$u_{il} \sim i.i.d.\ N(0,1)$	`gen e_n=rnormal(0,1)`	$E[u_{il}] = 0$
clustered error	$e_{il} = u_{il}(1 + v_i)$	`gen e_t1cc=e_t1*(1+e_cc)`	$E[e_{il}] = \gamma^{Euler}$, $\rho[e_{il}, v_i] > 0$

admission likelihood (implicit)	Uniform $U(0,1)$	`gen adm_base=runiform(0,1)`
		`gen adm=adm_base+(4-c)/3`
		`replace adm=1 if adm>1`
			$E[adm_{il} \mid c = 1] = 1$,
			$E[adm_{il} \mid c = 4] = 0.5$,
			$\rho[adm_{il}, c_i] < 0$

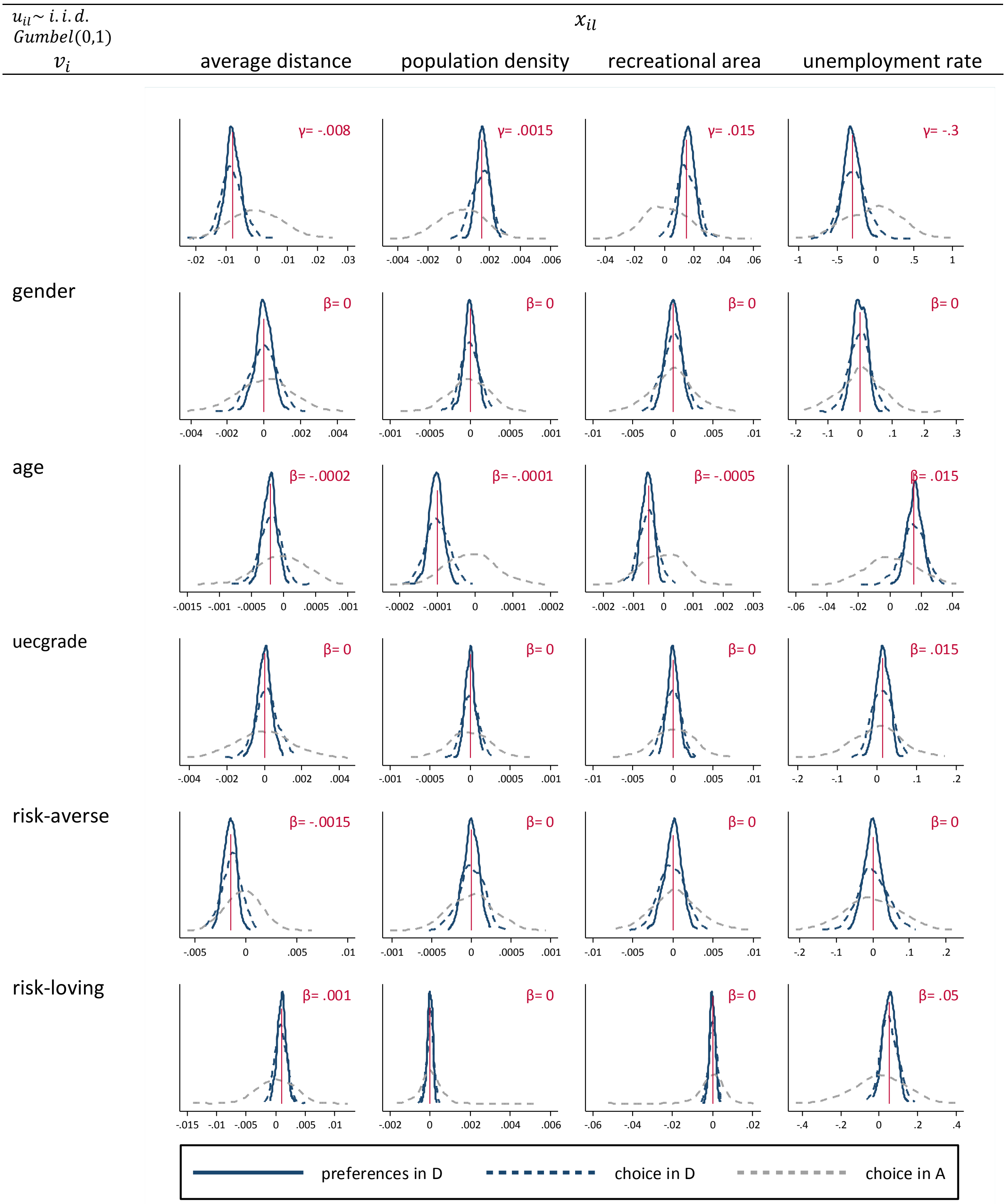
Note: The algorithm has been implemented with Stata 14.1 and seed set to 1218193708.

Table A4.2: Overall descriptive statistics for model variables in the empirical analyses

category	variable label	short description	original scale	N	min	max	mean	std.dev.	modified scale
x_{il}	*distance*	average distance from all postal code areas in an origin district to a potential destination	km	$(D \times n)$	0	859.07	288.94	141.73	
x_l	*total population*	INKAR 2012 data	cardinal, in 1000	164	34.06	3375.22	276.36	332.19	
	population density	INKAR 2012 data	cardinal	164	48.1	4468.3	831.27	833.01	
	GDP (per capita)	INKAR 2012 data	cardinal, 1000 €	164	17.4	106.2	37.72	16.03	
	price level / building prices	proxied by local building plot prices	cardinal, € per m^2	164	9.6	1292.6	179.63	187.36	
	share of recreational area	INKAR 2012 data	%	164	0.2	14.5	3.22	3.06	
	reg. centre reachability	travel time to next regional centre (based on the BBSR's reachability model), INKAR 2012 data	cardinal, min	164	0	76	18.37	19.12	
	unemployment rate	INKAR 2012 data	%	164	2.3	14.9	7.20	3.14	
	youth unemployment rate (<25 yrs.)	INKAR 2012 data	%	164	1.6	14.5	6.16	3.05	
	high-skilled employment rate	INKAR 2012 data	%	164	5.6	28.9	12.28	5.00	
	high-skilled employment rate (30-34 yrs.)	in relation to all employed, INKAR 2012 data	‰	164	6.1	78.2	23.39	14.98	
v_i									
socio-demographic	*gender*	1: female, 0: male	binary	1712	0	1	0.44	/	
	age	age in years	cardinal	1712	17	32	19.71	1.80	
	uecgrade	average grade (university entrance certificate; 1: best, 4: worst)	cardinal	1712	1.0	3.8	2.31	0.58	
	academic household	1 : at least one parent holds university degree, 0 : no parents with university degree	binary	1712	0	1	0.43	/	
	partnership	1: currently in a relationship, 0: no relationship	binary	1712	0	1	0.40	/	
	vocational training	1: vocational training completed, 0: otherwise	binary	1712	0	1	0.15	/	
previous mobility experiences	*residential move during school*	1: at least one residential move during school, 0: none	binary	1712	0	1	0.22	/	
	exchange participation	1 : exchange participation during school, 0 : otherwise	binary	1712	0	1	0.34	/	
	stay abroad	1 : at least one month spent abroad without family, 0: otherwise	binary	1712	0	1	0.21	/	
personality	*risk attitude (career domain)*	willingness to take risk in the career domain, 11-point scale (1: low, 11: high)	ordinal	1712	1	11	5.39	2.42	✓
	patience	willingness to bear costs in the present for future benefits, 7-point scale (1: low, 7: high)	ordinal	1712	1	7	5.44	1.17	✓
	Big-Five: extraversion	5-point scale (1: low, 5: high)	ordinal	1712	1	5	3.42	0.97	✓
	Big-Five: openness	5-point scale (1: low, 5: high)	ordinal	1712	1	5	3.20	1.03	✓
	Big-Five: neuroticism	5-point scale (1: low, 5: high)	ordinal	1712	1	5	2.83	0.91	✓
	Big-Five: conscientiousness	5-point scale (1: low, 5: high)	ordinal	1712	1	5	3.41	0.89	✓
	Big-Five: agreeableness	5-point scale (1: low, 5: high)	ordinal	1712	1	5	2.96	0.80	✓
	adaptability to new circumstance	ability to adapt to new circumstances, 7-point scale (1: low, 7: high)	ordinal	1712	1	7	3.94	1.53	✓
social preference	*importance of proximity (family)*	7-point scale (1: low, 7: high)	ordinal	1712	1	7	4.81	1.63	✓
	importance of proximity (friends)	7-point scale (1: low, 7: high)	ordinal	1712	1	7	5.05	1.41	✓

Note: Overall descriptive statistics are conditional on being in the estimation sample for the full model M4 discussed in Chapter 4.5. Destination-specific variables refer to the $D = 164$ potential destinations; individual-specific variables refer to the $n = 1712$ included subjects. Modified variables have been standardised and categorised into three distinct groups: those scoring low (score below the mean minus one standard deviation), the reference group of medium-type individuals (score within the range of one standard deviation around the mean) and those scoring high (score more than one standard deviation above the mean). INKAR data originates from the INKAR online database (http://www.inkar.de/), provided by the Federal Institute for Research on Building, Urban Affairs and Spatial Development (BBSR, 2014).

Figure A4.1: Kernel densities for simulated coefficients in the fully interacted specification (with type 1 extreme value specification)



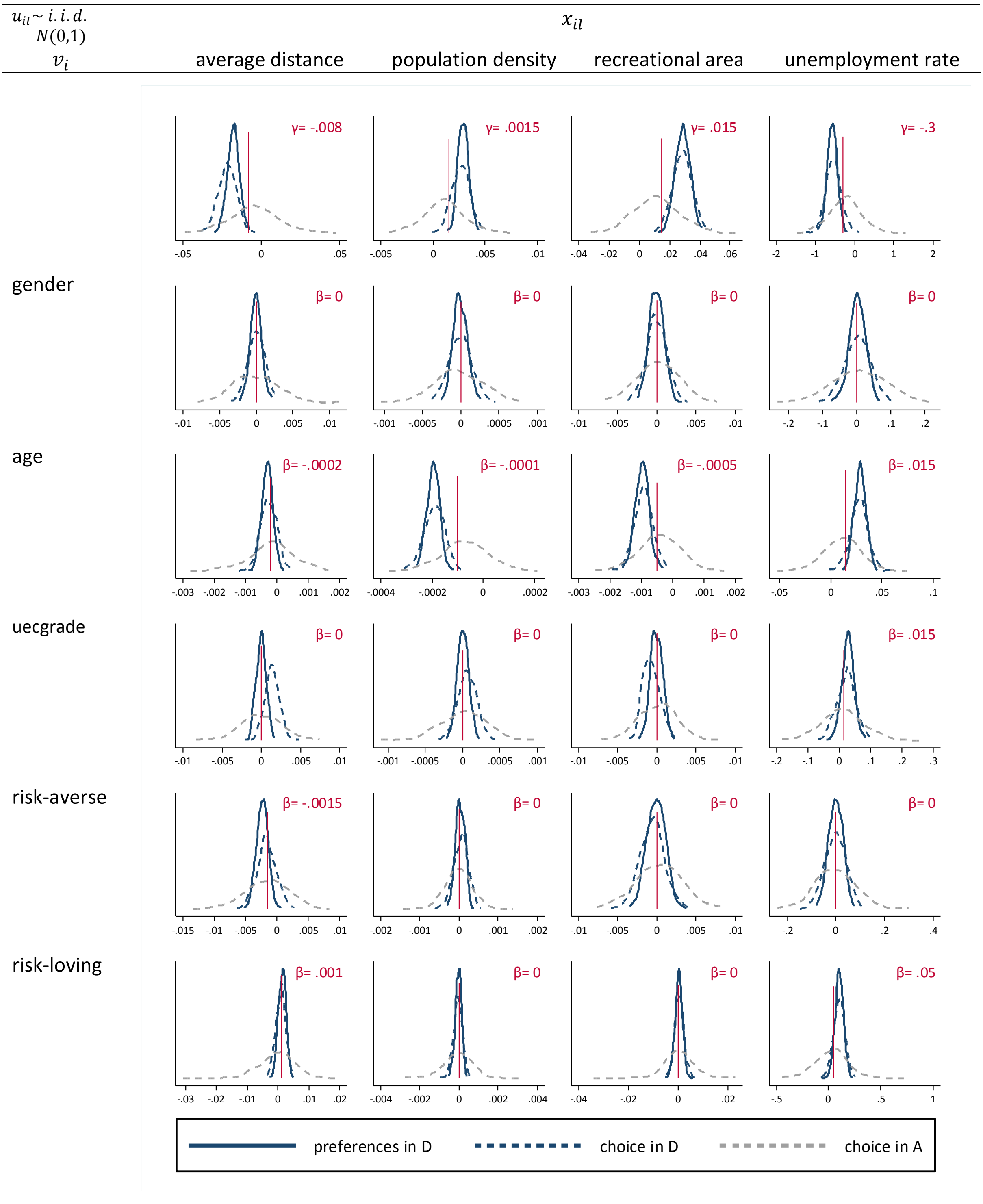
Note: Densities based on Epanechnikov kernels with optimal bandwidth. Coefficients β and γ indicate the true parameters in the main DGP. Illustrations in the first row refer to simulated coefficients for non-interacted location-specific variables x_{il}, panels in rows two to six show densities for the respective interactions of individual-specific variable v_i and x_{il}.

Table A4.3: Simulation results for varying information sets with error misspecification

$e_{il} \sim i.i.d.N(0,1)$		information set (estimated specification)								
		preferences in D (I)			choice in D (II)			choice in A (III)		
observed location choices		$S = 4$			$S = 1$			$S = 1$		
destination space		$D = 164$			$D = 164$			$A \in [2,4]$		
model	DGP	none	partial	full	none	partial	full	none	partial	full
$\boldsymbol{x_{il}}$: average distance	-0.0080	-0.02428	-0.01796	-0.01784	-0.02365	-0.02162	-0.02169	-0.00785	-0.00473	-0.00467
		(500)	(497)	(497)	(500)	(475)	(471)	(500)	(38)	(38)
gender # x_{il}	0		-0.00051	-0.00003		-0.0003	0.00003		-0.00038	-0.0001
			(44)	(27)		(18)	(16)		(20)	(21)
age # x_{il}	-0.0002		-0.00031	-0.00031		-0.00027	-0.00027		-0.00016	-0.00016
			(166)	(166)		(50)	(52)		(37)	(37)
uecgrade # x_{il}	0		-0.00002	-0.00001		0.00139	0.00139		-0.00001	0.00000
			(8)	(7)		(122)	(114)		(30)	(29)
risk-averse # x_{il}	-0.0015			-0.00234			-0.00164			-0.00165
				(318)			(63)			(41)
risk-loving # x_{il}	0.0010			0.00132			0.00083			-0.00019
				(93)			(29)			(18)
$\boldsymbol{x_l}$: population density	0.0015	-0.00095	0.0029	0.0029	-0.00095	0.00266	0.00266	-0.00029	0.00108	0.00108
		(500)	(500)	(500)	(500)	(432)	(429)	(264)	(53)	(57)
gender # x_l	0		0.00000	-0.00001		0.00001	-0.00001		-0.00003	-0.0003
			(22)	(18)		(22)	(20)		(21)	(23)
age # x_l	-0.0001		-0.0002	-0.0002		-0.00019	-0.00019		-0.00007	-0.00007
			(500)	(500)		(498)	(498)		(74)	(72)
uecgrade # x_l	0		0.00000	0.00000		0.00006	0.00006		0.00001	0.00002
			(21)	(22)		(37)	(37)		(18)	(20)
risk-averse # x_l	0			0.00003			0.00005			-0.00001
				(37)			(31)			(25)
risk-loving # x_l	0			-0.0004			-0.00006			-0.00006
				(26)			(27)			(24)
$\boldsymbol{x_l}$: recreational area (p.c.)	0.0150	0.00933	0.02872	0.02869	0.00841	0.02868	0.02869	0.00351	0.01134	0.01133
		(500)	(500)	(500)	(500)	(497)	(496)	(429)	(76)	(81)
gender # x_l	0		-0.0007	-0.00004		-0.00016	-0.00005		0.00018	0.00012
			(31)	(24)		(27)	(28)		(21)	(26)
age # x_l	-0.0005		-0.00097	-0.00097		-0.00093	-0.00093		-0.0004	-0.00041
			(495)	(496)		(443)	(446)		(60)	(57)
uecgrade # x_l	0		-0.00002	-0.00002		-0.00072	-0.00072		0.0001	0.00013
			(29)	(28)		(41)	(42)		(27)	(22)
risk-averse # x_l	0			-0.00009			-0.00061			0.00029
				(28)			(28)			(33)
risk-loving # x_l	0			0.0001			0.00036			0.00034
				(30)			(37)			(23)
$\boldsymbol{x_l}$: unemploy-ment rate	-0.3000	0.08311	-0.55595	-0.57188	0.08885	-0.51534	-0.53560	0.02247	-0.22672	-0.23355
		(500)	(498)	(499)	(498)	(395)	(404)	(47)	(56)	(55)
gender # x_l	0		-0.00826	0.00144		-0.00977	0.0023		0.00413	0.00718
			(30)	(24)		(31)	(23)		(19)	(25)
age # x_l	0.0150		0.02886	0.02883		0.02778	0.02776		0.01138	0.01156
			(500)	(499)		(447)	(445)		(53)	(54)
uecgrade # x_l	0.0150		0.02888	0.02893		0.02313	0.02301		0.01009	0.01029
			(146)	(147)		(55)	(54)		(20)	(21)
risk-averse # x_l	0			-0.00096			-0.00259			-0.00144
				(26)			(16)			(27)
risk-loving # x_l	0.0500			0.10337			0.10301			0.02995
				(388)			(262)			(24)

Note: The DGP-column presents the true parameters used in the data generating process (DGP). All results originate from a simulation, based on 500 replications and a simulated sample size of 1000 where the error has been deliberately mis-specified (normally distributed instead of type 1 extreme value). The first value in each cell is the average estimated coefficient, the second number stands for the number of estimated coefficients, which are significant at the 5 % level. Specifications 'none' are based solely on the vector x_{il} of location specific variables. Specifications labelled 'partial' draw on an interacted model ($v_i x_{il}$) without the two risk indicators. Specifications 'full' includes all (interacted) variables involved in the DGP. In case of the most restricted choice set, with $A \in [2,4]$, all simulated individuals with only one alternative have been dropped (no variation on the individual level). This reduced the sample by approximately one half.

Figure A4.2: Kernel densities for simulated coefficients in the fully interacted specification (with error misspecification)



Note: Densities based on Epanechnikov kernels with optimal bandwidth. Coefficients β and γ indicate the true parameters in the main DGP. Illustrations in the first row refer to simulated coefficients for non-interacted location-specific variables x_{il}, panels in row two to six show densities for the respective interactions of individual-specific variable v_i and x_{il}.

Table A4.4: Simulated average coefficients for varying information sets with clustered errors

$e_{il} = u_{il}(1 + v_i)$ $u_{il} \sim i.i.d.\ Gumbel(0,1)$ $v_i \sim i.i.d.\ U(-0.5,0.5)$		information set (estimated specification)								
		preferences in D (I)			choice in D (II)			choice in A (III)		
observed location choices		$S = 4$			$S = 1$			$S = 1$		
destination space		$D = 164$			$D = 164$			$A \in [2,4]$		
model	DGP	full u_{il}	full e_{il}	full e_{il} (c)	full u_{il}	full e_{il}	full e_{il} (c)	full u_{il}	full e_{il}	full e_{il} (c)
$\boldsymbol{x_{il}}$: average distance	-0.0080	-0.00791 (457)	-0.00824 (442)	-0.00824 (420)	-0.00817 (307)	-0.00688 (313)	-0.00688 (293)	0.00023 (24)	0.00014 (25)	0.00014 (21)
gender # x_{il}	0	0.00000 (25)	-0.00002 (50)	-0.00002 (28)	0.00000 (19)	-0.00002 (34)	-0.00002 (32)	0.00006 (25)	0.00006 (32)	0.00006 (30)
age # x_{il}	-0.0002	-0.00022 (245)	-0.0022 (242)	-0.0022 (190)	-0.0002 (103)	-0.0002 (100)	-0.0002 (92)	-0.00004 (22)	-0.00004 (21)	-0.00004 (22)
uecgrade # x_{il}	0	0.00001 (24)	0.00003 (48)	0.00003 (26)	0.00013 (25)	0.00017 (32)	0.00017 (28)	-0.00003 (27)	-0.00006 (28)	-0.00006 (28)
risk-averse # x_{il}	-0.0015	-0.0016 (391)	-0.00157 (372)	-0.00157 (310)	-0.00143 (149)	-0.00139 (145)	-0.00139 (128)	-0.00026 (26)	-0.0002 (21)	-0.0002 (22)
risk-loving # x_{il}	0.0010	0.00102 (141)	0.00098 (153)	0.00098 (116)	0.00087 (74)	0.00083 (72)	0.00083 (66)	-0.00002 (25)	-0.0001 (33)	-0.0001 (41)
$\boldsymbol{x_l}$: population density	0.0015	0.00157 (491)	0.00161 (484)	0.00161 (483)	0.00149 (312)	0.00152 (323)	0.00152 (325)	0.00019 (26)	0.00018 (31)	0.00018 (30)
gender # x_l	0	0.00000 (22)	0.00000 (32)	0.00000 (31)	0.00000 (20)	0.0000 (33)	0.0000 (27)	-0.00002 (24)	-0.00001 (24)	-0.00001 (28)
age # x_l	-0.0001	-0.0001 (500)	-0.00011 (500)	-0.00011 (500)	-0.0001 (454)	-0.0001 (454)	-0.0001 (454)	-0.00001 (24)	-0.00001 (20)	-0.00001 (23)
uecgrade # x_l	0	0.00000 (23)	0.00000 (32)	0.00000 (30)	0.00000 (20)	0.00000 (24)	0.00000 (27)	-0.00001 (24)	-0.00001 (28)	-0.00001 (29)
risk-averse # x_l	0	0.00000 (27)	0.00000 (23)	0.00000 (25)	0.00000 (27)	0.00000 (28)	0.00000 (32)	0.00000 (26)	0.00000 (30)	0.00000 (32)
risk-loving # x_l	0	-0.00001 (29)	-0.00001 (31)	-0.00001 (31)	-0.00001 (25)	-0.00001 (27)	-0.00001 (27)	0.00002 (16)	0.00002 (18)	0.00002 (25)
$\boldsymbol{x_l}$: recreational area (p.c.)	0.0150	0.01585 (481)	0.01683 (490)	0.01683 (492)	0.01517 (309)	0.01638 (358)	0.01638 (359)	0.00117 (31)	0.00234 (38)	0.00234 (40)
gender # x_l	0	0.00001 (33)	0.00004 (30)	0.00004 (30)	0.00001 (24)	0.00007 (26)	0.00007 (28)	-0.00003 (30)	0.00005 (25)	0.00005 (26)
age # x_l	-0.0005	-0.00053 (392)	-0.00056 (419)	-0.00056 (420)	-0.00051 (196)	-0.00054 (236)	-0.00054 (237)	-0.00005 (21)	-0.00009 (29)	-0.00009 (35)
uecgrade # x_l	0	0.00001 (27)	-0.00003 (21)	-0.00003 (23)	-0.0001 (21)	-0.00019 (32)	-0.00019 (34)	0.00011 (34)	0.00014 (22)	0.00014 (21)
risk-averse # x_l	0	-0.00001 (25)	-0.0001 (29)	-0.0001 (28)	-0.00014 (21)	-0.00025 (30)	-0.00025 (25)	0.00032 (27)	0.0019 (23)	0.0019 (29)
risk-loving # x_l	0	-0.00017 (27)	-0.00012 (30)	-0.00012 (32)	-0.00012 (24)	-0.00009 (26)	-0.00009 (31)	-0.0005 (20)	-0.0005 (20)	-0.0005 (32)
$\boldsymbol{x_l}$: unemploy-ment rate	-0.3000	-0.31507 (433)	-0.32967 (450)	-0.32967 (447)	-0.29240 (224)	-0.30883 (237)	-0.30883 (238)	-0.02989 (25)	-0.03788 (32)	-0.03788 (33)
gender # x_l	0	0.00124 (25)	0.00121 (30)	0.00121 (27)	0.00037 (27)	0.00117 (32)	0.00117 (31)	0.00142 (29)	0.00217 (26)	0.00217 (25)
age # x_l	0.0150	0.01576 (465)	0.01626 (471)	0.01626 (467)	0.1477 (265)	0.01527 (272)	0.01527 (264)	0.0012 (27)	0.00168 (27)	0.00168 (30)
uecgrade # x_l	0.0150	0.01475 (80)	0.01563 (77)	0.01563 (74)	0.01375 (33)	0.01491 (44)	0.01491 (45)	0.00329 (30)	0.00102 (31)	0.00102 (34)
risk-averse # x_l	0	-0.00089 (23)	0.00088 (21)	0.00088 (22)	-0.00073 (24)	-0.00058 (19)	-0.00058 (22)	-0.00237 (36)	-0.00374 (29)	-0.00374 (31)
risk-loving # x_l	0.0500	0.05338 (193)	0.05688 (209)	0.05688 (199)	0.05215 (114)	0.05604 (118)	0.05604 (118)	0.00386 (21)	0.01079 (27)	0.01079 (33)

Note: The DGP-column presents the true parameters used in the data generating process (DGP). All results originate from a simulation, based on 500 replications and a simulated sample size of 1000. Each presented specification 'full' includes all (interacted) variables involved in the DGP. Columns u_{il} depict results identical to Table 4.2 where errors in the DGP are not clustered on the individual level. Columns e_{il} show outcomes based on uncorrected standard errors for the same DGP, but with error correlation on the individual level. Columns e_{il} (c) are based on cluster robust variance-covariance estimators to account for intra-individual error correlation in the DGP. The first value in each cell is the average estimated coefficient, the second number stands for the number of estimated coefficients, which are significant at the 5 % level. In case of the most restricted choice set, with $A \in [2,4]$, all simulated individuals with only one alternative have been dropped (no variation on the individual level). This reduced the sample by approximately one half.

Table A4.5: Sequential model derivation for 'preferences in D'

dependent variable		preferences in D															
observed location choices		$S \leq 4$															
destination space		$D = 164$															
		OR	s.e.	OR	s.e.	OR	s.e.	OR	s.e.	OR	s.e.	OR	s.e.	OR	s.e.	OR	s.e.
x_{il}																	
distance		0.9885***	(0.0003)	0.9869***	(0.0004)	0.9755***	(0.0045)	0.9787***	(0.0048)	0.9802***	(0.0046)	0.9808***	(0.0045)	0.9831***	(0.0044)	0.9853***	(0.0039)
x_l																	
population				1.0015***	(0.0001)	1.0015***	(0.0001)	1.0015***	(0.0001)	1.0015***	(0.0001)	1.0015***	(0.0001)	1.0015***	(0.0001)		
population density				0.9986***	(0.0001)	0.9986***	(0.0001)	0.9986***	(0.0001)	0.9986***	(0.0001)	0.9986***	(0.0001)	0.9986***	(0.0001)		
GDP (per capita)				0.9948***	(0.0018)	0.9944***	(0.0018)	0.9942***	(0.0018)	0.9942***	(0.0018)	0.9941***	(0.0018)	0.9940***	(0.0018)		
price level (€/sq.)				1.0011***	(0.0002)	1.0012***	(0.0002)	1.0013***	(0.0002)	1.0013***	(0.0002)	1.0013***	(0.0002)	1.0013***	(0.0002)		
share of recreational area				1.1707***	(0.0113)	1.1696***	(0.0114)	1.1729***	(0.0114)	1.1741***	(0.0114)	1.1752***	(0.0114)	1.1767***	(0.0115)		
reg. centre reachability				0.9515***	(0.0020)	0.9514***	(0.0020)	0.9507***	(0.0020)	0.9507***	(0.0020)	0.9506***	(0.0020)	0.9506***	(0.0020)		
unemployment rate				1.1619***	(0.0204)	1.1610***	(0.0205)	1.1602***	(0.0206)	1.1605***	(0.0206)	1.1613***	(0.0206)	1.1601***	(0.0206)		
youth unemp. rate				0.9878	(0.0172)	0.9886	(0.0172)	0.9894	(0.0173)	0.9898	(0.0174)	0.9894	(0.0174)	0.9901	(0.0174)		
high-skilled emp. rate				0.9300***	(0.0070)	0.9313***	(0.0070)	0.9318***	(0.0071)	0.9322***	(0.0071)	0.9329***	(0.0070)	0.9336***	(0.0070)		
high-skilled emp. rate (<34)				1.0771***	(0.0030)	1.0767***	(0.0030)	1.0771***	(0.0030)	1.0772***	(0.0030)	1.0772***	(0.0030)	1.0773***	(0.0030)		
$v_i \# x_{il}$																	
female						1.0003	(0.0007)	0.9992	(0.0007)	0.9995	(0.0007)	0.9988*	(0.0007)	0.9988*	(0.0007)	0.9990*	(0.0006)
age						1.0007***	(0.0002)	1.0003	(0.0002)	1.0002	(0.0002)	1.0002	(0.0002)	1.0002	(0.0002)	1.0002	(0.0002)
uecgrade						0.9989*	(0.0006)	0.9996	(0.0006)	0.9997	(0.0006)	0.9998	(0.0006)	0.9995	(0.0006)	0.9991*	(0.0005)
academic household						1.0032***	(0.0007)	1.0025***	(0.0007)	1.0025***	(0.0007)	1.0026***	(0.0006)	1.0025***	(0.0006)	1.0017***	(0.0006)
in partnership						0.9974***	(0.0007)	0.9977***	(0.0007)	0.9976***	(0.0007)	0.9977***	(0.0007)	0.9978***	(0.0007)	0.9984***	(0.0006)
vocational education						0.9972**	(0.0013)	0.9984	(0.0012)	0.9983	(0.0012)	0.9983	(0.0012)	0.9987	(0.0012)	0.9993	(0.0010)
moved during school								1.0021***	(0.0008)	1.0019**	(0.0007)	1.0019**	(0.0007)	1.0019***	(0.0007)	1.0010	(0.0007)
exchange participation								1.0027***	(0.0007)	1.0027***	(0.0007)	1.0028***	(0.0007)	1.0027***	(0.0007)	1.0023***	(0.0006)
stay abroad								1.0056***	(0.0007)	1.0052***	(0.0007)	1.0052***	(0.0007)	1.0047***	(0.0007)	1.0038***	(0.0006)
risk attitude	low									0.9977***	(0.0007)	0.9980***	(0.0007)	0.9981***	(0.0007)	0.9986**	(0.0006)
	high									1.0001	(0.0010)	1.0003	(0.0010)	1.0001	(0.0010)	0.9998	(0.0009)
patience	low									0.9980**	(0.0010)	0.9982*	(0.0010)	0.9982*	(0.0010)	0.9982**	(0.0009)
	high									1.0021**	(0.0008)	1.0022**	(0.0009)	1.0016*	(0.0008)	1.0014*	(0.0007)
extraversion	low											0.9981*	(0.0011)	0.9987	(0.0011)	0.9985	(0.0010)
	high											0.9994	(0.0008)	0.9988	(0.0008)	0.9990	(0.0007)
openness	low											0.9986	(0.0008)	0.9987	(0.0009)	0.9989	(0.0008)
	high											1.0020**	(0.0008)	1.0018**	(0.0008)	1.0010	(0.0007)
neuroticism	low											0.9994	(0.0010)	0.9986	(0.0011)	0.9992	(0.0009)
	high											1.0010	(0.0009)	1.0014	(0.0009)	1.0014*	(0.0008)
conscientiousness	low											0.9995	(0.0008)	0.9997	(0.0008)	0.9998	(0.0007)
	high											0.9990	(0.0008)	0.9988	(0.0008)	0.9992	(0.0008)
agreeableness	low											0.9990	(0.0009)	0.9990	(0.0009)	0.9988	(0.0008)
	high											0.9998	(0.0008)	0.9999	(0.0008)	0.9998	(0.0007)
adaptability	low													0.9978**	(0.0009)	0.9987*	(0.0008)
	high													1.0032***	(0.0009)	1.0020**	(0.0008)
importance of	low															1.0018**	(0.0007)
proximity to family	high															0.9986	(0.0010)
importance of	low															1.0018**	(0.0008)
proximity to friends	high															0.9981*	(0.0010)
observations		$1712 \times D$		$1712 \times D$		$1712 \times D$		$1712 \times D$		$1712 \times D$		$1712 \times D$		$1712 \times D$		$1712 \times D$	
LL(0)		-21393.29		-21393.29		-21393.29		-21393.29		-21393.29		-21393.29		-21393.29		-21393.29	
LL		-17528.88		-13842.76		-13753.18		-13579.44		-13540.89		-13506.59		-13469.84		-17176.32	
df		1		11		17		20		24		34		36		30	
Wald χ^2		1553.63		5923.00		5977.80		6292.23		6450.21		6596.70		6622.09		1843.39	
prob $> \chi^2$		0.0000		0.0000		0.0000		0.0000		0.0000		0.0000		0.0000		0.0000	
pseudo R-squared		0.1806		0.3529		0.3571		0.3670		0.3652		0.3687		0.3704		0.1971	

*** p<0.01, ** p<0.05, * p<0.1

Note: Standard errors are clustered at the individual level. '#' indicates interactions between distance and individual-specific characteristics. The pseudo R-squared is calculated as $1 - LL/LL(0)$.

Table A4.6: Sequential model derivation for ‘choice in D’

dependent variable		choice in D															
observed location choices		$S=1$															
destination space		$D=164$															
		OR	s.e.	OR	s.e.	OR	s.e.	OR	s.e.	OR	s.e.	OR	s.e.	OR	s.e.	OR	s.e.
x_{il}																	
distance		0.9842***	(0.0005)	0.9801***	(0.0005)	0.9622***	(0.0062)	0.9648***	(0.0064)	0.9668***	(0.0062)	0.9685***	(0.0061)	0.9705***	(0.0062)	0.9702***	(0.0062)
x_l																	
population				1.0025***	(0.0001)	1.0025***	(0.0001)	1.0025***	(0.0001)	1.0025***	(0.0001)	1.0025***	(0.0001)	1.0025***	(0.0001)		
population density				0.9962***	(0.0001)	0.9962***	(0.0001)	0.9961***	(0.0001)	0.9961***	(0.0001)	0.9961***	(0.0001)	0.9961***	(0.0001)		
GDP (per capita)				1.0128***	(0.0019)	1.0134***	(0.0019)	1.0135***	(0.0019)	1.0134***	(0.0019)	1.0134***	(0.0019)	1.0137***	(0.0019)		
price level (€/sq.)				0.9969***	(0.0003)	0.9969***	(0.0003)	0.9971***	(0.0003)	0.9971***	(0.0003)	0.9971***	(0.0003)	0.9971***	(0.0003)		
share of recreational area				1.2942***	(0.0176)	1.3009***	(0.0181)	1.3031***	(0.0181)	1.3044***	(0.0181)	1.3054***	(0.0182)	1.3072***	(0.0183)		
reg. centre reachability				0.9157***	(0.0046)	0.9174***	(0.0045)	0.9178***	(0.0044)	0.9181***	(0.0044)	0.9183***	(0.0044)	0.9187***	(0.0044)		
unemployment rate				1.0265	(0.0298)	1.0419	(0.0305)	1.0509*	(0.0304)	1.0518*	(0.0303)	1.0538*	(0.0303)	1.0556*	(0.0304)		
youth unemp. rate				1.7830***	(0.0621)	1.7607***	(0.0611)	1.7487***	(0.0598)	1.7482***	(0.0595)	1.7453***	(0.0593)	1.7433***	(0.0591)		
high-skilled emp. rate				0.8548***	(0.0144)	0.8511***	(0.0144)	0.8483***	(0.0146)	0.8477***	(0.0146)	0.8476***	(0.0147)	0.8465***	(0.0147)		
high-skilled emp. rate (<34)				1.1752***	(0.0068)	1.1767***	(0.0069)	1.1776***	(0.0070)	1.1778***	(0.0070)	1.1779***	(0.0070)	1.1786***	(0.0070)		
$v_i\#x_{il}$																	
female						1.0004	(0.0009)	0.9994	(0.0009)	0.9996	(0.0009)	0.9992	(0.0010)	0.9989	(0.0010)	0.9993	(0.0010)
age						1.0003	(0.0003)	1.0000	(0.0003)	0.9999	(0.0003)	0.9998	(0.0003)	0.9998	(0.0003)	1.0002	(0.0003)
uecgrade						1.0053***	(0.0008)	1.0060***	(0.0008)	1.0060***	(0.0008)	1.0059***	(0.0009)	1.0055***	(0.0009)	1.0038***	(0.0009)
academic household						1.0022***	(0.0009)	1.0015*	(0.0009)	1.0014	(0.0009)	1.0014*	(0.0009)	1.0014	(0.0009)	1.0012	(0.0009)
in partnership						0.9974***	(0.0009)	0.9976***	(0.0009)	0.9976***	(0.0009)	0.9976***	(0.0009)	0.9976**	(0.0009)	0.9974***	(0.0010)
vocational education						0.9943***	(0.0017)	0.9955***	(0.0017)	0.9956***	(0.0017)	0.9960**	(0.0017)	0.9963**	(0.0017)	0.9961**	(0.0017)
moved during school								1.0023**	(0.0010)	1.0022**	(0.0010)	1.0022**	(0.0010)	1.0022**	(0.0010)	1.0012	(0.0010)
exchange participation								1.0028***	(0.0009)	1.0029***	(0.0009)	1.0030***	(0.0009)	1.0030***	(0.0009)	1.0031***	(0.0009)
stay abroad								1.0060***	(0.0009)	1.0055***	(0.0009)	1.0055***	(0.0010)	1.0049***	(0.0009)	1.0048***	(0.0010)
risk attitude	low									0.9976**	(0.0011)	0.9980*	(0.0011)	0.9981*	(0.0011)	0.9986	(0.0012)
	high									1.0013	(0.0012)	1.0015	(0.0013)	1.0013	(0.0013)	1.0011	(0.0013)
patience	low									0.9989	(0.0012)	0.9990	(0.0012)	0.9989	(0.0012)	0.9988	(0.0013)
	high									1.0030***	(0.0011)	1.0032***	(0.0011)	1.0022**	(0.0011)	1.0025**	(0.0011)
extraversion	low											0.9985	(0.0015)	0.9993	(0.0015)	0.9981	(0.0017)
	high											0.9997	(0.0011)	0.9989	(0.0011)	0.9986	(0.0011)
openness	low											0.9979*	(0.0011)	0.9980*	(0.0011)	0.9985	(0.0012)
	high											1.0018	(0.0011)	1.0016	(0.0011)	1.0004	(0.0011)
neuroticism	low											0.9988	(0.0014)	0.9978	(0.0014)	0.9982	(0.0014)
	high											0.9996	(0.0013)	1.0001	(0.0013)	1.0002	(0.0013)
conscientiousness	low											1.0000	(0.0010)	1.0002	(0.0010)	1.0008	(0.0011)
	high											0.9985	(0.0013)	0.9982	(0.0013)	0.9973*	(0.0014)
agreeableness	low											0.9987	(0.0011)	0.9986	(0.0011)	0.9978*	(0.0012)
	high											1.0016	(0.0011)	1.0015	(0.0011)	1.0020*	(0.0011)
adaptability	low													0.9974**	(0.0012)	0.9981	(0.0014)
	high													1.0044***	(0.0011)	1.0033***	(0.0011)
importance of	low															1.0030**	(0.0012)
proximity to family	high															0.9989	(0.0016)
importance of	low															1.0021	(0.0013)
proximity to friends	high															0.9993	(0.0017)
observations		$1712 \times D$		$1712 \times D$		$1712 \times D$		$1712 \times D$		$1712 \times D$		$1712 \times D$		$1712 \times D$		$1712 \times D$	
LL(0)		-8730.97		-8730.97		-8730.97		-8730.97		-8730.97		-8730.97		-8730.97		-8730.97	
LL		-6683.60		-4283.12		-4226.96		-4177.00		-4162.81		-4150.29		-4133.03		-6519.19	
df		1		11		17		20		24		34		36		30	
Wald χ^2		1126.99		5936.95		6374.05		6694.17		6741.43		6812.39		6785.50		1270.69	
prob $> \chi^2$		0.0000		0.0000		0.0000		0.0000		0.0000		0.0000		0.0000		0.0000	
pseudo R-squared		0.2345		0.5094		0.5159		0.5216		0.5232		0.5246		0.5266		0.2533	

*** p<0.01, ** p<0.05, * p<0.1

Note: Standard errors are clustered at the individual level. ‘#’ indicates interactions between distance and individual-specific characteristics. The pseudo R-squared is calculated as $1 - LL/LL(0)$.

Table A4.7: Robustness check – minimum sample analysis for varying information sets

dependent variable		preferences in D		choice in D		choice in A	
observed location choices		$S \leq 4$		$S = 1$		$S = 1$	
destination space		$D = 164$		$D = 164$		$A \in [2,4]$	
		OR	s.e.	OR	s.e.	OR	s.e.
x_{il}							
distance		0.9845***	(0.0051)	0.9755***	(0.0075)	1.0014	(0.0154)
x_l							
population		1.0015***	(0.0001)	1.0028***	(0.0001)	1.0012***	(0.0003)
population density		0.9989***	(0.0001)	0.9957***	(0.0001)	0.9949***	(0.0004)
GDP (per capita)		0.9938***	(0.0020)	1.0269***	(0.0027)	1.0053	(0.0151)
price level (€/sq.)		1.0010***	(0.0002)	0.9969***	(0.0003)	1.0000	(0.0014)
share of recreational area		1.1251***	(0.0129)	1.2494***	(0.0239)	1.3344***	(0.0523)
reg. centre reachability		0.9449***	(0.0025)	0.8861***	(0.0060)	0.9173***	(0.0193)
unemployment rate		1.1474***	(0.0235)	0.8418***	(0.0324)	1.3762***	(0.1618)
youth unemp. rate		0.9542**	(0.0192)	2.4461***	(0.1183)	2.3758***	(0.2840)
high-skilled emp. rate		0.9240***	(0.0075)	0.7288***	(0.0134)	0.5291***	(0.0459)
high-skilled emp. rate (<34)		1.0757***	(0.0032)	1.2492***	(0.0088)	1.3912***	(0.0430)
$v_i \# x_{il}$							
female		0.9991	(0.0007)	0.9999	(0.0010)	0.9950***	(0.0019)
age		1.0001	(0.0003)	0.9996	(0.0004)	0.9993	(0.0008)
uecgrade		0.9994	(0.0006)	1.0053***	(0.0010)	1.0001	(0.0017)
academic household		1.0024***	(0.0007)	1.0013	(0.0010)	1.0012	(0.0016)
in partnership		0.9980***	(0.0007)	0.9977**	(0.0010)	1.0001	(0.0018)
vocational education		0.9994	(0.0013)	0.9982	(0.0018)	1.0017	(0.0041)
moved during school		1.0019**	(0.0008)	1.0014	(0.0012)	0.9989	(0.0018)
exchange participation		1.0021***	(0.0007)	1.0030***	(0.0010)	1.0017	(0.0017)
stay abroad		1.0039***	(0.0008)	1.0041***	(0.0010)	1.0006	(0.0019)
risk attitude	low	0.9980***	(0.0008)	0.9970**	(0.0012)	0.9978	(0.0021)
	high	0.9993	(0.0011)	1.0001	(0.0015)	1.0022	(0.0025)
patience	low	0.9985	(0.0010)	0.9988	(0.0015)	0.9922**	(0.0031)
	high	1.0014	(0.0009)	1.0014	(0.0012)	0.9979	(0.0023)
extraversion	low	0.9997	(0.0012)	1.0011	(0.0016)	0.9966	(0.0030)
	high	0.9994	(0.0008)	0.9999	(0.0012)	0.9998	(0.0021)
openness	low	0.9986	(0.0009)	0.9977*	(0.0013)	0.9943**	(0.0022)
	high	1.0022***	(0.0008)	1.0021*	(0.0012)	1.0043**	(0.0019)
neuroticism	low	0.9989	(0.0011)	0.9974*	(0.0014)	0.9962	(0.0031)
	high	1.0012	(0.0009)	1.0005	(0.0013)	0.9975	(0.0022)
conscientiousness	low	0.9993	(0.0009)	0.9984	(0.0013)	1.0000	(0.0022)
	high	0.9987	(0.0009)	0.9979	(0.0013)	1.0061***	(0.0022)
agreeableness	low	0.9986	(0.0009)	0.9978*	(0.0012)	1.0024	(0.0025)
	high	0.9994	(0.0009)	1.0010	(0.0012)	1.0050***	(0.0019)
adaptability	low	0.9981**	(0.0010)	0.9976*	(0.0014)	1.0045**	(0.0021)
	high	1.0026***	(0.0009)	1.0049***	(0.0012)	1.0058***	(0.0022)
importance of proximity	low	1.0018**	(0.0009)	1.0029**	(0.0013)	1.0035*	(0.0021)
to family	high	0.9990	(0.0012)	1.0008	(0.0016)	1.0026	(0.0034)
importance of proximity	low	1.0027***	(0.0009)	1.0032**	(0.0015)	1.0006	(0.0023)
to friends	high	0.9982	(0.0013)	0.9997	(0.0017)	0.9989	(0.0031)
observations		$1139 \times D$		$1139 \times D$		$1139 \times \bar{A}$	
LL(0)		-16933.39		-5808.75		-1259.80	
LL		-10802.15		-2603.18		-478.13	
df		40		40		40	
Wald χ^2		5115.83		3949.27		576.39	
prob $> \chi^2$		0.0000		0.0000		0.0000	
pseudo R-squared		0.3621		0.5519		0.6205	

*** p<0.01, ** p<0.05, * p<0.1

Note: Standard errors are clustered at the individual level. '#' indicates interactions between distance and individual-specific characteristics. The pseudo R-squared is calculated as $1 - LL/LL(0)$.

Table A4.8: Robustness check – preferences and choices for alternative definitions of the destination space

dependent variable		preferences in D								choice in D							
observed location choices		$S \leq 4$								$S = 1$							
destination space		$D_U = 71$				D_S=101				$D_U = 71$				D_S=101			
		OR	s.e.	OR	s.e.	OR	s.e.	OR	s.e.	OR	s.e.	OR	s.e.	OR	s.e.	OR	s.e.
x_{il}																	
distance		0.9876***	(0.0003)	0.9841***	(0.0042)	0.9874***	(0.0003)	0.9835***	(0.0042)	0.9809***	(0.0005)	0.9726***	(0.0061)	0.9804***	(0.0005)	0.9720***	(0.0058)
x_l																	
population		1.0013***	(0.0000)	1.0014***	(0.0000)	1.0014***	(0.0000)	1.0014***	(0.0000)	1.0020***	(0.0001)	1.0020***	(0.0001)	1.0021***	(0.0001)	1.0021***	(0.0001)
population density		0.9987***	(0.0001)	0.9987***	(0.0001)	0.9986***	(0.0001)	0.9985***	(0.0001)	0.9963***	(0.0001)	0.9962***	(0.0001)	0.9962***	(0.0001)	0.9961***	(0.0001)
GDP (per capita)		0.9954*	(0.0026)	0.9950**	(0.0026)	0.9861***	(0.0025)	0.9854***	(0.0025)	1.0341***	(0.0032)	1.0340***	(0.0028)	1.0223***	(0.0025)	1.0225***	(0.0024)
price level (€/sq.)		1.0018***	(0.0002)	1.0019***	(0.0002)	1.0020***	(0.0002)	1.0021***	(0.0002)	0.9974***	(0.0003)	0.9975***	(0.0003)	0.9979***	(0.0003)	0.9980***	(0.0003)
share of recreational area		1.1724***	(0.0108)	1.1778***	(0.0110)	1.1656***	(0.0111)	1.1718***	(0.0113)	1.2462***	(0.0147)	1.2655***	(0.0158)	1.2701***	(0.0166)	1.2854***	(0.0175)
reg. centre reachability		0.9666***	(0.0030)	0.9662***	(0.0031)	0.9627***	(0.0021)	0.9617***	(0.0021)	0.9321***	(0.0069)	0.9365***	(0.0065)	0.9426***	(0.0049)	0.9432***	(0.0047)
unemployment rate		1.1801***	(0.0271)	1.1790***	(0.0270)	1.1576***	(0.0205)	1.1517***	(0.0206)	1.2326***	(0.0369)	1.2443***	(0.0353)	1.2233***	(0.0319)	1.2266***	(0.0320)
youth unemp. rate		0.9237***	(0.0207)	0.9207***	(0.0210)	1.0011	(0.0167)	1.0034	(0.0171)	1.6714***	(0.0633)	1.6536***	(0.0612)	1.7625***	(0.0592)	1.7397***	(0.0592)
high-skilled emp. rate		0.9504***	(0.0096)	0.9576***	(0.0097)	0.8877***	(0.0085)	0.8926***	(0.0085)	0.7747***	(0.0185)	0.7622***	(0.0188)	0.7659***	(0.0170)	0.7645***	(0.0173)
high-skilled emp. rate (<34)		1.0395***	(0.0036)	1.0390***	(0.0036)	1.0909***	(0.0040)	1.0905***	(0.0039)	1.1825***	(0.0100)	1.1890***	(0.0103)	1.2222***	(0.0107)	1.2211***	(0.0108)
$v_i \# x_{il}$																	
female				0.9990	(0.0006)			0.9990	(0.0006)			0.9993	(0.0009)			0.9993	(0.0009)
age				1.0001	(0.0002)			1.0002	(0.0002)			0.9997	(0.0003)			0.9997	(0.0003)
uecgrade				0.9995	(0.0006)			0.9994	(0.0006)			1.0052***	(0.0008)			1.0051***	(0.0008)
academic household				1.0021***	(0.0006)			1.0022***	(0.0006)			1.0010	(0.0008)			1.0011	(0.0008)
in partnership				0.9982***	(0.0007)			0.9982***	(0.0007)			0.9982**	(0.0009)			0.9981**	(0.0009)
vocational education				0.9991	(0.0011)			0.9992	(0.0012)			0.9964**	(0.0016)			0.9967**	(0.0016)
moved during school				1.0014*	(0.0007)			1.0015**	(0.0007)			1.0017*	(0.0010)			1.0016*	(0.0010)
exchange participation				1.0024***	(0.0006)			1.0025***	(0.0006)			1.0026***	(0.0009)			1.0026***	(0.0009)
stay abroad				1.0044***	(0.0007)			1.0044***	(0.0007)			1.0047***	(0.0009)			1.0045***	(0.0009)
risk attitude	low			0.9984**	(0.0007)			0.9982**	(0.0007)			0.9983	(0.0011)			0.9983	(0.0011)
	high			0.9999	(0.0010)			0.9998	(0.0010)			1.0009	(0.0012)			1.0009	(0.0012)
patience	low			0.9981**	(0.0010)			0.9981**	(0.0009)			0.9987	(0.0012)			0.9990	(0.0012)
	high			1.0016**	(0.0008)			1.0018**	(0.0008)			1.0024**	(0.0011)			1.0025**	(0.0011)
extraversion	low			0.9988	(0.0011)			0.9990	(0.0011)			0.9998	(0.0015)			0.9997	(0.0014)
	high			0.9990	(0.0007)			0.9990	(0.0007)			0.9989	(0.0010)			0.9990	(0.0010)
openness	low			0.9986*	(0.0008)			0.9986*	(0.0008)			0.9980*	(0.0011)			0.9980*	(0.0011)
	high			1.0016**	(0.0008)			1.0016**	(0.0008)			1.0013	(0.0011)			1.0013	(0.0011)
neuroticism	low			0.9987	(0.0010)			0.9988	(0.0010)			0.9976*	(0.0013)			0.9978	(0.0013)
	high			1.0010	(0.0008)			1.0012	(0.0008)			0.9997	(0.0012)			0.9997	(0.0012)
conscientiousness	low			0.9998	(0.0008)			0.9997	(0.0008)			1.0003	(0.0010)			1.0002	(0.0010)
	high			0.9988	(0.0008)			0.9989	(0.0008)			0.9977*	(0.0013)			0.9980	(0.0013)
agreeableness	low			0.9989	(0.0008)			0.9988	(0.0008)			0.9979*	(0.0011)			0.9982*	(0.0011)
	high			1.0000	(0.0008)			0.9998	(0.0008)			1.0014	(0.0011)			1.0015	(0.0011)
adaptability	low			0.9983*	(0.0009)			0.9984*	(0.0009)			0.9978*	(0.0012)			0.9979*	(0.0012)
	high			1.0023***	(0.0009)			1.0024***	(0.0009)			1.0038***	(0.0011)			1.0036***	(0.0011)
importance of	low			1.0019**	(0.0008)			1.0020**	(0.0008)			1.0031***	(0.0012)			1.0030***	(0.0011)
proximity to family	high			0.9987	(0.0011)			0.9984	(0.0011)			0.9989	(0.0015)			0.9991	(0.0015)
importance of	low			1.0018**	(0.0009)			1.0019**	(0.0009)			1.0020	(0.0013)			1.0019	(0.0012)
proximity to friends	high			0.9981	(0.0012)			0.9982	(0.0012)			0.9999	(0.0016)			0.9999	(0.0016)
observations		$1712 \times D_U$		$1712 \times D_U$		$1712 \times D_S$		$1712 \times D_S$		$1712 \times D_U$		$1712 \times D_U$		$1712 \times D_S$		$1712 \times D_S$	
LL(0)		-17040.49		-17040.49		-19045.63		-19045.63		-7297.71		-7297.71		-7901.09		-7901.09	
LL		-12295.32		-11914.47		-13201.70		-12790.82		-3943.64		-3785.93		-4098.40		-3943.70	
df		11		40		11		40		11		40		11		40	
Wald χ^2		3467.40		3727.70		4622.33		5090.36		4440.57		4119.59		5434.11		5749.37	
prob > χ^2		0.0000		0.0000		0.0000		0.0000		0.0000		0.0000		0.0000		0.0000	
pseudo R-squared		0.2785		0.3008		0.3068		0.3284		0.4596		0.4812		0.4813		0.5009	

*** p<0.01, ** p<0.05, * p<0.1

Note: Standard errors are clustered at the individual level. '#' indicates interactions between distance and individual-specific characteristics. The first restricted potential destination space D_U composes only of locations with a university on site (excluding those with exclusively universities of applied sciences). The second modification D_S includes only those potential destinations that have either been finally chosen or were selected into the three most preferred alternatives at the application or the final selection stage by at least on subject in the sample. The corresponding results for the baseline destination space $D = 164$ can be found in Table A4.5 and Table A4.6, respectively.

Table A4.9: Robustness check – programme selectivity

dependent variable		preferences in D								choice in D							
observed location choices		$S \leq 4$								$S = 1$							
destination space		$D = 164$								$D = 164$							
sample (study programmes)		full		restricted (only Business Studies and Economics and Business)						full		restricted (only Business Studies and Economics and Business)					
		OR	s.e.	OR	s.e.	OR	s.e.	OR	s.e.	OR	s.e.	OR	s.e.	OR	s.e.	OR	s.e.
x_{il}																	
distance		0.9830***	(0.0043)	0.9859***	(0.0004)	0.9860***	(0.0048)	0.9892**	(0.0045)	0.9695***	(0.0060)	0.9788***	(0.0006)	0.9735***	(0.0076)	0.9761***	(0.0073)
x_l																	
population		1.0015***	(0.0001)	1.0015***	(0.0001)	1.0015***	(0.0001)	1.0015***	(0.0001)	1.0025***	(0.0001)	1.0024***	(0.0001)	1.0024***	(0.0001)	1.0024***	(0.0001)
population density		0.9986***	(0.0001)	0.9987***	(0.0001)	0.9987***	(0.0001)	0.9987***	(0.0001)	0.9961***	(0.0001)	0.9966***	(0.0001)	0.9965***	(0.0001)	0.9965***	(0.0001)
GDP (per capita)		0.9939***	(0.0018)	0.9920***	(0.0022)	0.9914***	(0.0022)	0.9912***	(0.0022)	1.0138***	(0.0019)	1.0103***	(0.0021)	1.0111***	(0.0021)	1.0112***	(0.0021)
price level (€/sq.)		1.0013***	(0.0002)	1.0013***	(0.0002)	1.0014***	(0.0002)	1.0014***	(0.0002)	0.9971***	(0.0003)	0.9961***	(0.0004)	0.9962***	(0.0004)	0.9963***	(0.0004)
share of recreational area		1.1764***	(0.0115)	1.1376***	(0.0124)	1.1383***	(0.0125)	1.1423***	(0.0126)	1.3074***	(0.0183)	1.2195***	(0.0177)	1.2274***	(0.0183)	1.2327***	(0.0185)
reg. centre reachability		0.9505***	(0.0021)	0.9514***	(0.0022)	0.9508***	(0.0022)	0.9507***	(0.0022)	0.9187***	(0.0044)	0.9221***	(0.0046)	0.9236***	(0.0045)	0.9244***	(0.0044)
unemployment rate		1.1563***	(0.0205)	1.1672***	(0.0226)	1.1670***	(0.0228)	1.1660***	(0.0230)	1.0542*	(0.0304)	1.0538	(0.0336)	1.0761**	(0.0342)	1.0806**	(0.0341)
youth unemp. rate		0.9919	(0.0175)	0.9936	(0.0196)	0.9952	(0.0196)	0.9969	(0.0198)	1.7445***	(0.0590)	1.7554***	(0.0665)	1.7232***	(0.0645)	1.7178***	(0.0636)
high-skilled emp. rate		0.9340***	(0.0070)	0.9327***	(0.0082)	0.9339***	(0.0083)	0.9363***	(0.0082)	0.8468***	(0.0147)	0.9048***	(0.0190)	0.8993***	(0.0191)	0.8978***	(0.0192)
high-skilled emp. rate (<34)		1.0773***	(0.0030)	1.0756***	(0.0035)	1.0756***	(0.0035)	1.0757***	(0.0035)	1.1785***	(0.0070)	1.1538***	(0.0081)	1.1558***	(0.0082)	1.1568***	(0.0083)
$v_i \# x_{il}$																	
female		0.9990	(0.0007)			0.9991	(0.0008)	0.9992	(0.0008)	0.9992	(0.0009)			0.9993	(0.0011)	0.9992	(0.0011)
age		1.0002	(0.0002)			1.0000	(0.0002)	0.9999	(0.0002)	0.9998	(0.0003)			0.9996	(0.0004)	0.9995	(0.0004)
uecgrade		0.9994	(0.0006)			0.9987*	(0.0007)	0.9988*	(0.0007)	1.0054***	(0.0009)			1.0053***	(0.0010)	1.0048***	(0.0011)
academic household		1.0023***	(0.0006)			1.0025***	(0.0007)	1.0025***	(0.0007)	1.0011	(0.0009)			1.0009	(0.0010)	1.0009	(0.0010)
in partnership		0.9981***	(0.0007)			0.9968***	(0.0008)	0.9972***	(0.0008)	0.9979**	(0.0009)			0.9973**	(0.0011)	0.9978**	(0.0011)
vocational education		0.9991	(0.0012)			1.0004	(0.0013)	1.0010	(0.0012)	0.9966**	(0.0016)			0.9974	(0.0018)	0.9985	(0.0018)
moved during school		1.0015**	(0.0007)			1.0015*	(0.0009)	1.0009	(0.0009)	1.0018*	(0.0010)			1.0024**	(0.0012)	1.0021*	(0.0012)
exchange participation		1.0026***	(0.0007)			1.0024***	(0.0008)	1.0026***	(0.0008)	1.0028***	(0.0009)			1.0024**	(0.0010)	1.0027**	(0.0010)
stay abroad		1.0045***	(0.0007)			1.0059***	(0.0008)	1.0046***	(0.0008)	1.0049***	(0.0009)			1.0063***	(0.0011)	1.0049***	(0.0011)
risk attitude	low	0.9982**	(0.0007)					0.9982**	(0.0008)	0.9982*	(0.0011)					0.9976*	(0.0013)
	high	0.9999	(0.0010)					0.9999	(0.0013)	1.0011	(0.0013)					0.9999	(0.0017)
patience	low	0.9982*	(0.0010)					0.9984	(0.0011)	0.9989	(0.0012)					0.9999	(0.0014)
	high	1.0018**	(0.0008)					1.0023**	(0.0009)	1.0023**	(0.0011)					1.0028**	(0.0013)
extraversion	low	0.9989	(0.0011)					0.9970**	(0.0014)	0.9995	(0.0015)					0.9985	(0.0020)
	high	0.9990	(0.0008)					1.0000	(0.0009)	0.9990	(0.0010)					0.9997	(0.0012)
openness	low	0.9986	(0.0009)					0.9994	(0.0010)	0.9981*	(0.0011)					0.9983	(0.0013)
	high	1.0017**	(0.0008)					1.0019**	(0.0009)	1.0014	(0.0011)					1.0018	(0.0013)
neuroticism	low	0.9988	(0.0010)					0.9986	(0.0012)	0.9978	(0.0014)					0.9987	(0.0017)
	high	1.0012	(0.0009)					1.0005	(0.0011)	0.9998	(0.0013)					0.9993	(0.0015)
conscientiousness	low	0.9997	(0.0008)					0.9999	(0.0010)	1.0002	(0.0010)					1.0007	(0.0013)
	high	0.9989	(0.0008)					0.9995	(0.0009)	0.9981	(0.0013)					0.9984	(0.0015)
agreeableness	low	0.9988	(0.0009)					0.9998	(0.0010)	0.9981*	(0.0011)					0.9987	(0.0013)
	high	0.9999	(0.0008)					1.0000	(0.0009)	1.0016	(0.0011)					1.0020	(0.0013)
adaptability	low	0.9984*	(0.0009)					0.9978**	(0.0010)	0.9979*	(0.0012)					0.9976*	(0.0014)
	high	1.0025***	(0.0009)					1.0017	(0.0011)	1.0036***	(0.0011)					1.0037***	(0.0014)
importance of	low	1.0020**	(0.0008)					1.0012	(0.0010)	1.0031***	(0.0012)					1.0023	(0.0015)
proximity to family	high	0.9985	(0.0011)					0.9983	(0.0012)	0.9993	(0.0015)					1.0001	(0.0017)
importance of	low	1.0020**	(0.0009)					1.0019*	(0.0011)	1.0020	(0.0013)					1.0017	(0.0017)
proximity to friends	high	0.9981	(0.0012)					0.9974*	(0.0013)	0.9998	(0.0016)					0.9993	(0.0019)
observations		$1712 \times D$		$1391 \times D$		$1391 \times D$		$1391 \times D$		$1712 \times D$		$1391 \times D$		$1391 \times D$		$1391 \times D$	
LL(0)		-21393.29		-17311.63		-17311.63		-17311.63		-8730.97		-7093.91		-7093.91		-7093.91	
LL		-13411.59		-10998.41		-10778.32		-10657.72		-4116.20		-3526.19		-3457.01		-3413.90	
df		40		11		20		40		40		11		20		40	
Wald χ^2		6624.60		4606.04		4847.57		5072.73		6793.91		3860.25		4426.86		4582.03	
prob $> \chi^2$		0.0000		0.0000		0.0000		0.0000		0.0000		0.0000		0.0000		0.0000	
pseudo R-squared		0.3731		0.3647		0.3774		0.3844		0.5286		0.5029		0.5127		0.5188	

*** p<0.01, ** p<0.05, * p<0.1

Note: Standard errors are clustered at the individual level. '#' indicates interactions between distance and individual-specific characteristics. This table reports results for the full and a restricted sample consisting only of the two most similar and widely available programmes (Business Studies, Economics and Business).

Table A4.10: Destination preferences and choices in a model of maximum individual-level conditioning (including labour market sorting patterns)

dependent variable			preferences in D		choice in D						choice in A	
observed location choices			$S \leq 4$		$S = 1$						$S = 1$	
destination space			$D = 164$		$D = 164$		$D_U = 71$		D_S=101		$A \in [2,4]$	
			OR	s.e.	OR	s.e.	OR	s.e.	OR	s.e.	OR	s.e.
x_{il}												
distance			0.9829***	(0.0043)	0.9689***	(0.0061)	0.9720***	(0.0061)	0.9714***	(0.0059)	0.9989	(0.0159)
x_l												
population			1.0015***	(0.0001)	1.0025***	(0.0001)	1.0021***	(0.0001)	1.0022***	(0.0001)	1.0013***	(0.0003)
population density			0.9986***	(0.0001)	0.9961***	(0.0001)	0.9962***	(0.0001)	0.9961***	(0.0001)	0.9948***	(0.0004)
GDP (per capita)			0.9946**	(0.0024)	1.0133***	(0.0028)	1.0345***	(0.0043)	1.0218***	(0.0032)	0.9989	(0.0203)
price level (€/sq.)			1.0015***	(0.0002)	0.9978***	(0.0004)	0.9982***	(0.0004)	0.9988***	(0.0004)	1.0026*	(0.0016)
share of recreational area			1.1781***	(0.0115)	1.3131***	(0.0186)	1.2698***	(0.0161)	1.2906***	(0.0177)	1.3430***	(0.0519)
reg. centre reachability			0.9506***	(0.0021)	0.9185***	(0.0044)	0.9360***	(0.0065)	0.9433***	(0.0047)	0.9171***	(0.0189)
unemployment rate			1.1846***	(0.0287)	1.0637	(0.0443)	1.2767***	(0.0572)	1.2404***	(0.0493)	1.4213**	(0.2181)
youth unemp. rate			0.9612	(0.0236)	1.7095***	(0.0821)	1.5994***	(0.0870)	1.7090***	(0.0833)	2.1829***	(0.3316)
high-skilled emp. rate			0.9330***	(0.0101)	0.8587***	(0.0217)	0.7765***	(0.0261)	0.7743***	(0.0234)	0.5897***	(0.0609)
high-skilled emp. rate (<34)			1.0772***	(0.0039)	1.1721***	(0.0096)	1.1812***	(0.0128)	1.2155***	(0.0133)	1.3399***	(0.0474)
$v_i \# x_{il}$												
female			0.9990	(0.0007)	0.9992	(0.0010)	0.9992	(0.0009)	0.9993	(0.0009)	0.9951**	(0.0019)
age			1.0002	(0.0002)	0.9998	(0.0003)	0.9998	(0.0003)	0.9998	(0.0003)	0.9995	(0.0008)
uecgrade			0.9994	(0.0006)	1.0054***	(0.0009)	1.0052***	(0.0008)	1.0051***	(0.0008)	0.9998	(0.0017)
academic household			1.0023***	(0.0006)	1.0012	(0.0009)	1.0010	(0.0008)	1.0012	(0.0008)	1.0015	(0.0017)
in partnership			0.9981***	(0.0007)	0.9980**	(0.0009)	0.9982**	(0.0009)	0.9981**	(0.0009)	0.9996	(0.0018)
vocational education			0.9991	(0.0012)	0.9965**	(0.0016)	0.9963**	(0.0016)	0.9966**	(0.0016)	1.0025	(0.0043)
moved during school			1.0015**	(0.0007)	1.0018*	(0.0010)	1.0017*	(0.0010)	1.0016*	(0.0010)	0.9990	(0.0019)
exchange participation			1.0026***	(0.0007)	1.0029***	(0.0009)	1.0026***	(0.0009)	1.0027***	(0.0009)	1.0021	(0.0017)
stay abroad			1.0045***	(0.0007)	1.0048***	(0.0009)	1.0046***	(0.0009)	1.0045***	(0.0009)	1.0004	(0.0019)
risk attitude		low	0.9980***	(0.0008)	0.9976*	(0.0014)	0.9979	(0.0013)	0.9977*	(0.0013)	0.9982	(0.0022)
		high	1.0000	(0.0011)	1.0014	(0.0017)	1.0010	(0.0016)	1.0012	(0.0017)	1.0011	(0.0028)
patience		low	0.9979**	(0.0010)	0.9968**	(0.0016)	0.9967**	(0.0015)	0.9968**	(0.0015)	0.9871***	(0.0043)
		high	1.0020**	(0.0009)	1.0034**	(0.0014)	1.0033**	(0.0013)	1.0036***	(0.0014)	0.9985	(0.0023)
extraversion		low	0.9989	(0.0011)	0.9996	(0.0015)	0.9998	(0.0015)	0.9997	(0.0014)	0.9967	(0.0030)
		high	0.9990	(0.0008)	0.9990	(0.0010)	0.9988	(0.0010)	0.9990	(0.0010)	1.0007	(0.0021)
openness		low	0.9986	(0.0009)	0.9981	(0.0011)	0.9980*	(0.0011)	0.9981*	(0.0011)	0.9941***	(0.0022)
		high	1.0017**	(0.0008)	1.0015	(0.0011)	1.0014	(0.0011)	1.0014	(0.0011)	1.0033*	(0.0019)
neuroticism		low	0.9988	(0.0010)	0.9977	(0.0014)	0.9976*	(0.0013)	0.9978	(0.0013)	0.9960	(0.0031)
		high	1.0012	(0.0009)	0.9997	(0.0012)	0.9997	(0.0012)	0.9996	(0.0012)	0.9979	(0.0023)
conscientiousness		low	0.9997	(0.0008)	1.0002	(0.0011)	1.0004	(0.0010)	1.0003	(0.0010)	1.0004	(0.0022)
		high	0.9989	(0.0008)	0.9981	(0.0013)	0.9978*	(0.0013)	0.9981	(0.0013)	1.0052**	(0.0021)
agreeableness		low	0.9988	(0.0009)	0.9982	(0.0011)	0.9980*	(0.0011)	0.9982	(0.0011)	1.0025	(0.0024)
		high	1.0000	(0.0008)	1.0016	(0.0011)	1.0014	(0.0011)	1.0016	(0.0011)	1.0051**	(0.0020)
adaptability		low	0.9983*	(0.0009)	0.9979*	(0.0012)	0.9979*	(0.0012)	0.9979*	(0.0012)	1.0033	(0.0021)
		high	1.0024***	(0.0009)	1.0037***	(0.0012)	1.0039***	(0.0011)	1.0037***	(0.0011)	1.0068***	(0.0022)
importance of proximity		low	1.0020**	(0.0008)	1.0030**	(0.0012)	1.0030**	(0.0012)	1.0029***	(0.0011)	1.0027	(0.0020)
to family		high	0.9985	(0.0011)	0.9991	(0.0015)	0.9987	(0.0015)	0.9989	(0.0015)	1.0022	(0.0035)
importance of proximity		low	1.0020**	(0.0009)	1.0020	(0.0013)	1.0020	(0.0013)	1.0020	(0.0013)	1.0011	(0.0021)
to friends		high	0.9981	(0.0012)	1.0000	(0.0016)	1.0000	(0.0016)	1.0000	(0.0015)	0.9991	(0.0032)
$v_i \# x_l$												
GDP (pc) #	risk attitude	low	0.9998	(0.0035)	1.0016	(0.0043)	1.0002	(0.0063)	1.0025	(0.0041)	1.0289	(0.0279)
		high	1.0010	(0.0040)	0.9971	(0.0070)	0.9972	(0.0086)	0.9982	(0.0065)	1.0355	(0.0260)
	patience	low	0.9943	(0.0038)	0.9928	(0.0056)	0.9952	(0.0074)	0.9972	(0.0050)	0.9844	(0.0490)
		high	0.9992	(0.0035)	1.0071	(0.0047)	1.0032	(0.0070)	1.0032	(0.0046)	0.9817	(0.0348)
price level #	risk attitude	low	0.9996	(0.0004)	0.9992	(0.0006)	0.9991	(0.0006)	0.9988*	(0.0006)	0.9973	(0.0021)
		high	0.9995	(0.0005)	1.0003	(0.0007)	1.0000	(0.0008)	1.0005	(0.0008)	0.9945	(0.0036)
	patience	low	0.9993	(0.0004)	0.9977***	(0.0008)	0.9972***	(0.0010)	0.9972***	(0.0009)	0.9901**	(0.0046)
		high	1.0002	(0.0004)	0.9987**	(0.0006)	0.9990	(0.0007)	0.9993	(0.0007)	0.9949	(0.0037)
unemp. rate #	risk attitude	low	0.9244**	(0.0342)	0.9094	(0.0674)	0.8674	(0.0789)	0.9092	(0.0710)	0.8080	(0.2148)
		high	0.9950	(0.0574)	1.0405	(0.0996)	1.0639	(0.1152)	1.0254	(0.1009)	1.0162	(0.3720)
	patience	low	0.9436	(0.0436)	1.0477	(0.0853)	1.0677	(0.1060)	1.0703	(0.0895)	0.9575	(0.3312)
		high	1.0361	(0.0433)	1.0120	(0.0747)	0.9463	(0.0866)	0.9839	(0.0773)	1.2090	(0.3487)
youth unemp.	risk attitude	low	1.0704*	(0.0420)	1.1633*	(0.0923)	1.1985*	(0.1179)	1.1586*	(0.0980)	1.3567	(0.3599)
Rate #		high	1.0038	(0.0613)	0.9555	(0.0957)	0.9688	(0.1177)	0.9954	(0.1064)	1.1943	(0.4558)
	patience	low	1.1234**	(0.0541)	1.0071	(0.0865)	0.9739	(0.1046)	0.9756	(0.0878)	1.2813	(0.4394)
		high	0.9772	(0.0441)	0.9331	(0.0765)	0.9894	(0.1022)	0.9382	(0.0816)	0.9853	(0.3015)
high-skilled	risk attitude	low	1.0375**	(0.0182)	0.9826	(0.0398)	0.9865	(0.0517)	0.9722	(0.0457)	0.8295	(0.1394)
emp. rate #		high	1.0161	(0.0259)	0.9801	(0.0534)	0.9465	(0.0693)	0.9603	(0.0569)	0.9362	(0.1955)
	patience	low	0.9895	(0.0245)	1.0977*	(0.0564)	1.0828	(0.0721)	1.1111*	(0.0625)	0.9408	(0.2297)
		high	0.9602**	(0.0182)	0.8987***	(0.0359)	0.9039*	(0.0485)	0.9157**	(0.0411)	0.4758***	(0.1181)
high-skilled	risk attitude	low	0.9939	(0.0056)	1.0175	(0.0134)	1.0168	(0.0164)	1.0199	(0.0160)	1.0570	(0.0533)
emp rate		high	0.9926	(0.0078)	1.0001	(0.0165)	1.0118	(0.0206)	1.0094	(0.0191)	1.0798	(0.0834)
(<34 yrs) #	patience	low	1.0096	(0.0078)	0.9793	(0.0155)	0.9800	(0.0189)	0.9734	(0.0173)	1.0823	(0.0841)
		high	1.0066	(0.0061)	1.0264**	(0.0131)	1.0248	(0.0162)	1.0207	(0.0154)	1.2209***	(0.0866)
observations			$1712 \times D$		$1712 \times D$		$1712 \times D_U$		$1712 \times D_S$		$1139 \times \bar{A}$	
LL(0)			-21393.29		-8730.97		-7297.71		-7901.09		-1259.80	
LL			-13388.34		-4092.43		-3764.37		-3920.43		-462.00	
df			64		64		64		64		64	
Wald χ^2			7104.18		6817.76		4195.65		5806.43		585.44	
prob $> \chi^2$			0.0000		0.0000		0.0000		0.0000		0.0000	
pseudo R-squared			0.3742		0.5313		0.4842		0.5038		0.6333	

*** p<0.01, ** p<0.05, * p<0.1

Note: Standard errors are clustered at the individual level. '#' indicates interactions between distance and individual-specific characteristics. $\bar{A} \approx 3.1370$ is the average number of observed alternatives in the admission set of those 1139 individuals whose admission set included more than one alternative. The pseudo R-squared is calculated as $1 - LL/LL(0)$.

Table A4.11: Distribution of coefficient estimates for the Hausman-McFadden test

dependent variable		choice in D								
observed location choices		$S = 1$								
destination space		$D = 164$								
		full destination space		restricted destination space ($D_R = 163$)						
				β_R						no. of significant β_R ($\alpha = 0.1$)
		coeff.	s.e.	mean (coeff.)	standard deviation	min	max	$q = 0.05$	$q = 0.95$	
x_{il}										
distance		-0.0309***	(0.0062)	-0.0310	0.0021	-0.0569	-0.0274	-0.0311	-0.0303	164
x_l										
population		0.0025***	(0.0001)	0.0025	0.0002	0.0017	0.0035	0.0024	0.0025	164
population density		-0.0039***	(0.0001)	-0.0039	0.0002	-0.0052	-0.0028	-0.0039	-0.0038	164
GDP (per capita)		0.0137***	(0.0019)	0.0135	0.0039	-0.0227	0.0323	0.0118	0.0149	163
price level (€/sq.)		-0.0029***	(0.0003)	-0.0030	0.0015	-0.0211	-0.0015	-0.0033	-0.0025	164
share of recreational area		0.2680***	(0.0140)	0.2683	0.0262	0.1423	0.5615	0.2627	0.2695	164
reg. centre reachability		-0.0848***	(0.0048)	-0.0851	0.0053	-0.1241	-0.0653	-0.0886	-0.0828	164
unemployment rate		0.0527*	(0.0288)	0.0513	0.0434	-0.2915	0.2563	0.0259	0.0766	142
youth unemp. rate		0.5565***	(0.0338)	0.5572	0.0564	0.3028	1.1568	0.5233	0.5952	164
high-skilled emp. rate		-0.1663***	(0.0174)	-0.1656	0.0396	-0.4356	0.2338	-0.1826	-0.1554	164
high-skilled emp. rate (<34)		0.1642***	(0.0060)	0.1641	0.0135	0.0378	0.2723	0.1604	0.1701	164
$v_i \# x_{il}$										
female		-0.0008	(0.0009)	-0.0007	0.0001	-0.0013	0.0001	-0.0008	-0.0007	0
age		-0.0002	(0.0003)	-0.0002	0.0000	-0.0003	0.0000	-0.0002	-0.0002	0
uecgrade		0.0054***	(0.0008)	0.0054	0.0005	0.0026	0.0108	0.0053	0.0054	164
academic household		0.0011	(0.0009)	0.0011	0.0001	0.0003	0.0017	0.0011	0.0012	1
in partnership		-0.0021**	(0.0009)	-0.0021	0.0001	-0.0025	-0.0007	-0.0021	-0.0020	163
vocational education		-0.0034**	(0.0016)	-0.0034	0.0006	-0.0097	-0.0012	-0.0035	-0.0033	162
moved during school		0.0018*	(0.0010)	0.0018	0.0001	0.0006	0.0022	0.0018	0.0018	162
exchange participation		0.0028***	(0.0009)	0.0028	0.0002	0.0009	0.0034	0.0028	0.0028	163
stay abroad		0.0049***	(0.0009)	0.0049	0.0002	0.0024	0.0057	0.0048	0.0049	163
risk attitude	low	-0.0018*	(0.0011)	-0.0018	0.0001	-0.0027	-0.0011	-0.0019	-0.0018	139
	high	0.0011	(0.0013)	0.0011	0.0002	0.0000	0.0026	0.0010	0.0011	1
patience	low	-0.0011	(0.0012)	-0.0011	0.0001	-0.0019	-0.0004	-0.0011	-0.0010	0
	high	0.0023**	(0.0011)	0.0023	0.0001	0.0011	0.0029	0.0023	0.0024	162
extraversion	low	-0.0005	(0.0015)	-0.0005	0.0002	-0.0014	0.0007	-0.0006	-0.0005	0
	high	-0.0010	(0.0010)	-0.0010	0.0001	-0.0014	-0.0003	-0.0010	-0.0010	0
openness	low	-0.0019*	(0.0011)	-0.0019	0.0001	-0.0025	-0.0015	-0.0020	-0.0019	159
	high	0.0014	(0.0011)	0.0014	0.0001	0.0002	0.0018	0.0014	0.0014	0
neuroticism	low	-0.0023	(0.0014)	-0.0022	0.0002	-0.0037	-0.0011	-0.0023	-0.0022	11
	high	-0.0002	(0.0013)	-0.0002	0.0002	-0.0012	0.0009	-0.0002	-0.0002	0
conscientiousness	low	0.0002	(0.0010)	0.0002	0.0001	-0.0005	0.0014	0.0001	0.0002	0
	high	-0.0019	(0.0013)	-0.0019	0.0001	-0.0030	-0.0012	-0.0020	-0.0019	2
agreeableness	low	-0.0019*	(0.0011)	-0.0019	0.0001	-0.0025	-0.0008	-0.0019	-0.0018	150
	high	0.0016	(0.0011)	0.0016	0.0001	0.0008	0.0031	0.0015	0.0016	2
adaptability	low	-0.0021*	(0.0012)	-0.0021	0.0001	-0.0029	-0.0013	-0.0021	-0.0021	160
	high	0.0036***	(0.0011)	0.0036	0.0002	0.0023	0.0049	0.0036	0.0036	164
importance of proximity	low	0.0031***	(0.0012)	0.0031	0.0001	0.0019	0.0036	0.0031	0.0031	163
to family	high	-0.0007	(0.0015)	-0.0007	0.0002	-0.0023	0.0003	-0.0008	-0.0007	0
importance of proximity	low	0.0020	(0.0013)	0.0020	0.0002	0.0012	0.0034	0.0019	0.0020	1
to friends	high	-0.0002	(0.0016)	-0.0002	0.0001	-0.0006	0.0005	-0.0002	-0.0001	0
observations		$1712 \times D$		$I_R \times D_R$						
LL(0)		-8730.97		-8667.33	294.85	-8720.50	-5857.81	-8720.50	-8720.50	
LL		-4116.20		-4074.49	190.79	-4116.20	-2297.90	-4116.18	-4029.24	
df		40								40
Wald χ^2		6793.91		6800.06	736.12	2365.19	13684.55	6257.24	7063.87	
prob > χ^2		0.0000		0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	
pseudo R-squared		0.5286		0.5302	0.0091	0.5261	0.6077	0.5280	0.5353	

*** p<0.01, ** p<0.05, * p<0.1

Note: The restricted destination space is always of size $D_R = D - 1 = 163$, since in each of the 164 restricted samples one alternative is excluded. The relevant restricted sample size varies, such that $I_R \in [1150,1712]$. Reported values for estimated coefficients in the restricted destination space are always aggregates for the 164 restricted samples. The same holds for the estimation diagnostics aside from the number of observations and the model degrees of freedom. Standard errors are clustered at the individual level. '#' indicates interactions between distance and individual-specific characteristics. The pseudo R-squared is calculated as $1 - LL/LL(0)$.

Table A4.12: Competing destinations framework – choices for alternative definitions of the destination space

dependent variable		choice in D								choice in D							
observed location choices		$S = 1$								$S = 1$							
destination space		$D_U = 71$								D_S=101							
		OR	s.e.	OR	s.e.	OR	s.e.	OR	s.e.	OR	s.e.	OR	s.e.	OR	s.e.	OR	s.e.
x_{il}																	
distance		0.9825***	(0.0006)	0.9727***	(0.0067)	0.9705***	(0.0059)	0.9778***	(0.0063)	0.9822 ***	(0.0006)	0.9728***	(0.0061)	0.9706***	(0.0060)	0.9776***	(0.0059)
x_l																	
population		1.0033***	(0.0003)	1.0033***	(0.0003)			1.0032***	(0.0002)	1.0037 ***	(0.0002)	1.0037***	(0.0002)			1.0037***	(0.0002)
population density		0.9947***	(0.0001)	0.9947***	(0.0001)			0.9947***	(0.0001)	0.9941 ***	(0.0001)	0.9941***	(0.0001)			0.9941***	(0.0001)
GDP (per capita)		1.0841***	(0.0067)	1.0833***	(0.0065)			1.0863***	(0.0061)	1.0452 ***	(0.0039)	1.0444***	(0.0037)			1.0449***	(0.0038)
price level (€/sq.)		0.9912***	(0.0004)	0.9914***	(0.0004)			0.9913***	(0.0004)	0.9955 ***	(0.0004)	0.9956***	(0.0004)			0.9957***	(0.0004)
share of recreational area		1.2886***	(0.0136)	1.2984***	(0.0139)			1.3022***	(0.0141)	1.3259 ***	(0.0149)	1.3309***	(0.0151)			1.3331***	(0.0152)
reg. centre reachability		0.9065***	(0.0147)	0.9116***	(0.0138)			0.9148***	(0.0134)	0.8990 ***	(0.0101)	0.8998***	(0.0098)			0.9012***	(0.0097)
unemployment rate		2.0712***	(0.1416)	2.0897***	(0.1347)			2.1152***	(0.1330)	1.7350 ***	(0.0934)	1.7623***	(0.0924)			1.7768***	(0.0917)
youth unemp. rate		1.2814***	(0.0630)	1.2782***	(0.0614)			1.2826***	(0.0613)	1.6498 ***	(0.0791)	1.6193***	(0.0755)			1.6195***	(0.0746)
high-skilled emp. rate		0.7019***	(0.0224)	0.6946***	(0.0220)			0.6912***	(0.0218)	0.6632 ***	(0.0212)	0.6650***	(0.0209)			0.6641***	(0.0208)
high-skilled emp. rate (<34)		1.2650***	(0.0162)	1.2703***	(0.0161)			1.2743***	(0.0162)	1.3239 ***	(0.0170)	1.3218***	(0.0168)			1.3234***	(0.0168)
$v_i \# x_{il}$																	
female				0.9991	(0.0009)	0.9993	(0.0010)	0.9991	(0.0010)			0.9994	(0.0009)	0.9993	(0.0010)	0.9992	(0.0009)
age				0.9997	(0.0004)	1.0001	(0.0003)	0.9995	(0.0003)			0.9997	(0.0003)	1.0001	(0.0003)	0.9995	(0.0003)
uecgrade				1.0062***	(0.0009)	1.0040***	(0.0009)	1.0055***	(0.0009)			1.0063***	(0.0009)	1.0041***	(0.0009)	1.0057***	(0.0009)
academic household				1.0013	(0.0009)	1.0012	(0.0009)	1.0010	(0.0009)			1.0013	(0.0008)	1.0012	(0.0009)	1.0010	(0.0009)
in partnership				0.9979**	(0.0009)	0.9975***	(0.0009)	0.9983*	(0.0009)			0.9978**	(0.0009)	0.9975***	(0.0010)	0.9982**	(0.0009)
vocational education				0.9944***	(0.0019)	0.9965**	(0.0016)	0.9955**	(0.0018)			0.9947***	(0.0018)	0.9961**	(0.0017)	0.9958**	(0.0017)
moved during school				1.0026**	(0.0010)	1.0013	(0.0010)	1.0018*	(0.0010)			1.0022**	(0.0010)	1.0012	(0.0010)	1.0015	(0.0010)
exchange participation				1.0027***	(0.0009)	1.0030***	(0.0009)	1.0027***	(0.0009)			1.0026***	(0.0009)	1.0030***	(0.0009)	1.0027***	(0.0009)
stay abroad				1.0053***	(0.0010)	1.0049***	(0.0009)	1.0041***	(0.0010)			1.0051***	(0.0009)	1.0048***	(0.0009)	1.0039***	(0.0010)
risk attitude	low					0.9987	(0.0011)	0.9980*	(0.0012)					0.9988	(0.0011)	0.9981*	(0.0011)
	high					1.0011	(0.0013)	1.0002	(0.0012)					1.0011	(0.0012)	0.9999	(0.0012)
patience	low					0.9989	(0.0013)	0.9988	(0.0014)					0.9990	(0.0013)	0.9993	(0.0013)
	high					1.0025**	(0.0011)	1.0031***	(0.0011)					1.0026**	(0.0011)	1.0030***	(0.0011)
extraversion	low					0.9985	(0.0016)	1.0004	(0.0015)					0.9982	(0.0016)	1.0003	(0.0014)
	high					0.9986	(0.0010)	0.9991	(0.0011)					0.9986	(0.0011)	0.9994	(0.0011)
openness	low					0.9986	(0.0012)	0.9975**	(0.0012)					0.9984	(0.0012)	0.9974**	(0.0011)
	high					1.0005	(0.0011)	1.0009	(0.0011)					1.0005	(0.0011)	1.0010	(0.0011)
neuroticism	low					0.9981	(0.0014)	0.9974*	(0.0014)					0.9981	(0.0014)	0.9978	(0.0014)
	high					1.0000	(0.0013)	0.9997	(0.0013)					1.0001	(0.0013)	0.9995	(0.0012)
conscientiousness	low					1.0006	(0.0011)	1.0004	(0.0010)					1.0007	(0.0011)	1.0001	(0.0010)
	high					0.9973**	(0.0014)	0.9975*	(0.0014)					0.9974*	(0.0014)	0.9979	(0.0013)
agreeableness	low					0.9979*	(0.0011)	0.9979*	(0.0011)					0.9979*	(0.0011)	0.9983	(0.0011)
	high					1.0018	(0.0011)	1.0018*	(0.0011)					1.0018	(0.0011)	1.0018*	(0.0011)
adaptability	low					0.9981	(0.0013)	0.9978*	(0.0013)					0.9980	(0.0014)	0.9976**	(0.0012)
	high					1.0031***	(0.0011)	1.0042***	(0.0011)					1.0033***	(0.0011)	1.0040***	(0.0011)
importance of proximity to family	low					1.0031***	(0.0012)	1.0028**	(0.0012)					1.0030***	(0.0012)	1.0027**	(0.0011)
	high					0.9989	(0.0015)	0.9984	(0.0017)					0.9990	(0.0015)	0.9988	(0.0016)
importance of proximity to friends	low					1.0021	(0.0013)	1.0020	(0.0013)					1.0020	(0.0013)	1.0018	(0.0012)
	high					0.9995	(0.0016)	0.9998	(0.0018)					0.9994	(0.0016)	0.9998	(0.0017)
$\ln A_l$: accessibility of l		✓		✓		✓		✓		✓		✓		✓		✓	
observations		$1712 \times D_U$		$1712 \times D_U$		$1712 \times D_U$		$1712 \times D_U$		$1712 \times D_S$		$1712 \times D_S$		$1712 \times D_S$		$1712 \times D_S$	
LL(0)		-7297.71		-7297.71		-7297.71		-7297.71		-7901.09		-7901.09		-7901.09		-7901.09	
LL		-3641.39		-3554.23		-5223.35		-3495.64		-3681.41		-3600.46		-5912.73		-3548.52	
df		12		21		31		41		12		21		31		41	
Wald χ^2		4029.08		3940.33		1484.96		3983.95		11619.98		8715.11		1516.65		9779.34	
prob $> \chi^2$		0.0000		0.0000		0.0000		0.0000		0.0000		0.0000		0.0000		0.0000	
pseudo R-squared		0.5010		0.5130		0.2842		0.5210		0.5341		0.5443		0.2517		0.5509	

*** p<0.01, ** p<0.05, * p<0.1

Note: Standard errors are clustered at the individual level. '#' indicates interactions between distance and individual specific characteristics. The first restricted potential destination space D_U composes only of locations with a university on site (excluding those with exclusively universities of applied sciences). The second modification D_S includes only those potential destinations that have either been finally chosen or were selected into the three most preferred alternatives at the application or the final selection stage by at least on subject in the sample. The corresponding results for the baseline destination space $D = 164$ can be found in Table 4.3.

Table A5.1: Descriptive statistics for model variables

category	variable label	short description	scale	N	min	max	mean	std.dev.	modified scale
$y_{i,t+1}$	*residential move*	occurrence of a residential move from t to $t+1$ (SOEP-Geocode)	binary	10793	0	1	0.084	/	
	distance	distance between old and new address (SOEP-Geocode)	km	10793	0	761.758	3.915	34.324	
x_{ilt}	*distance*	conditional logit approach: distance between RPU centroids	km	75936	0	785.454	315.356	155.387	
x_{lt}	*total population*	Gemeindeverzeichnis-Informationssystem	cardinal, in 1000	576	201.783	3501.872	848.4222	626.809	
	population density	INKAR	cardinal	576	1.023	865	210.884	173.334	
	GDP (per capita)	INKAR	cardinal, 1000 €	576	17	57.2	29.965	7.364	
	share of recreational area	INKAR	%	576	0.3	12.0	1.452	1.680	
	unemployment rate	INKAR	%	576	2.2	16.1	7.316	3.238	
	high-skilled employment rate	INKAR	%	576	4.7	23.7	9.859	3.217	
v_{it}^{soc}	*gender*	1: female, 0: male	binary	10793	0	1	0.602	/	
	age	age in years	cardinal	10793	18	64	44.725	11.837	
	partnership	1: currently in a relationship, 0: no relationship	binary	10793	0	1	0.301	/	
	educational attainment	0: middle vocational or below; 1: secondary (vocational, Abitur or higher vocational); 2: tertiary (based on pgisced97)	ordinal	10793	0	2	/	/	
	kids	number of children living in HH	cardinal	10793	0	6	0.305	0.688	
	HH income	household income	cardinal	10793	0	40000	1712.614	1288.591	
	own dwelling	ownership of dwelling (based on hgowner)	binary	10793	0	1	0.238	/	
v_{it}^{lab}	*labour market participation*	1: full-time; 2: part-time; 3: not working	ordinal	10793	1	3	/	/	
	unemployment experience	cumulative months of previous unemployment spells	cardinal	10793	0	37	1.974	3.635	
v_{it}^{sat}	*satisfaction with overall life*	11-point scale (0: completely dissatisfied; 10: completely satisfied)	ordinal	10793	0	10	6.535	1.869	✓
	satisfaction with HH income	11-point scale (0: completely dissatisfied; 10: completely satisfied)	ordinal	10793	0	10	5.571	2.531	✓
	satisfaction with dwelling	11-point scale (0: completely dissatisfied; 10: completely satisfied)	ordinal	10793	0	10	7.295	1.993	✓
v_{it}^{mob}	*previous moves*	total number of recorded residential moves (since 2001)	binary	10793	0	10	0.964	1.215	
	covered distance	sum of recorded covered distance (since 2001)	binary	10793	0	1467.635	39.931	126.241	
v_{it}^{pers}	*extraversion*	Big-Five trait; 7-point scale (1: low; 7: high); 2009 and 2013	ordinal	3560	1	7	4.852	1.146	✓
	neuroticism	Big- Five trait; 7-point scale (1: low; 7: high); 2009 and 2013	ordinal	3567	1	7	4.614	1.233	✓
	openness	Big- Five trait; 7-point scale (1: low; 7: high); 2009 and 2013	ordinal	3569	1	7	3.792	1.238	✓
	conscientiousness	Big- Five trait; 7-point scale (1: low; 7: high); 2009 and 2013	ordinal	3563	1	7	5.800	0.913	✓
	agreeableness	Big- Five trait; 7-point scale (1: low; 7: high); 2009 and 2013	ordinal	3561	1	7	5.392	0.930	✓
	patience	11-point scale (0: very impatient; 10: very patient); 2008 and 2013	ordinal	3710	0	10	5.165	2.169	✓
	risk attitude	willingness to take risks, 11-point scale (0: low; 10: high)	ordinal	10793	0	10	4.562	2.246	✓

Note: Reported figures are pooled descriptive statistics from the sample time horizon 2008-2014. More specifically, variables indexed t refer to 2008-2013, outcome variables indexed $t+1$ to 2009-2014. Outcome variables $y_{i,t+1}$ are reported for the full sample of 10793 person-year observations, as are individual level variables v_{it}. Reported statistics for the destination specific variables x_{lt} refer to the 96 unique regional planning units (RPU) over the time horizon 2008-2012, yielding 576 destination-year observations. Distances to potential destinations (x_{ilt}) are recorded for 75936 person-destination-year combinations. If a summary statistic for a specific variable does not have any meaningful interpretation, '/' is displayed. Modified variables have been standardised and categorised into three distinct groups: those scoring low (score below the mean minus one standard deviation), the reference group of medium-type individuals (score within the range of one standard deviation around the mean) and those scoring high (score more than one standard deviation above the mean).

Table A5.2: Moving likelihood in the binary destination space – sequential model derivation

dependent variable		$y_{i,t+1}^{move}$															
model		pooled logit															
time horizon		6 years						2 years				1 year					
		OR	s.e.	OR	s.e.	OR	s.e.	OR	s.e.	OR	s.e.	OR	s.e.	OR	s.e.	OR	s.e.
v_i^{soc}	gender (female=1)	1.3487***	(0.1120)	1.3617***	(0.1159)	1.3460***	(0.1115)	1.3731**	(0.2008)	1.2941*	(0.1966)	1.4309	(0.3171)	1.3971	(0.3215)	1.3725	(0.3149)
	age (years)	0.9569***	(0.0032)	0.9547***	(0.0034)	0.9624***	(0.0035)	0.9621***	(0.0061)	0.9618***	(0.0062)	0.9526***	(0.0089)	0.9530***	(0.0091)	0.9521***	(0.0090)
	educational attainment																
	secondary	0.9458	(0.1090)	0.9711	(0.1140)	0.9746	(0.1124)	1.0237	(0.2126)	0.9689	(0.2058)	0.9282	(0.2888)	0.9062	(0.2920)	0.9433	(0.3044)
	tertiary	0.8844	(0.0836)	0.9248	(0.0887)	0.8882	(0.0846)	0.9754	(0.1581)	0.9384	(0.1546)	1.2076	(0.2781)	1.1964	(0.2843)	1.2613	(0.3040)
	number of kids in HH	0.9227	(0.0482)	0.8725**	(0.0471)	0.8811**	(0.0461)	0.7138***	(0.0907)	0.7092***	(0.0915)	0.7832	(0.1373)	0.7908	(0.1424)	0.7942	(0.1436)
	HH income	1.0000	(0.0000)	1.0000	(0.0000)	1.0000	(0.0000)	1.0000	(0.0001)	1.0000	(0.0001)	1.0000	(0.0001)	1.0000	(0.0001)	1.0001	(0.0001)
	partnership	1.0582	(0.0798)	1.0250	(0.0785)	1.0223	(0.0785)	0.9569	(0.1333)	0.9467	(0.1339)	0.8295	(0.1681)	0.8420	(0.1719)	0.8329	(0.1720)
	dwelling ownership	0.3463***	(0.0475)	0.3918***	(0.0541)	0.4304***	(0.0596)	0.4292***	(0.1077)	0.4301***	(0.1084)	0.4920*	(0.1894)	0.4837*	(0.1889)	0.4820*	(0.1883)
v_i^{lab}	labour market participation																
	full-time	0.6700***	(0.0705)	0.6812***	(0.0730)	0.6556***	(0.0683)	0.7006*	(0.1299)	0.6950*	(0.1313)	0.4897***	(0.1332)	0.4929**	(0.1374)	0.4948**	(0.1383)
	part-time	0.9120	(0.0908)	0.9151	(0.0928)	0.8957	(0.0901)	1.0138	(0.1891)	1.0002	(0.1894)	0.8251	(0.2222)	0.8374	(0.2254)	0.8553	(0.2328)
	unempl. exp. (months)	0.9644**	(0.0137)	0.9570***	(0.0141)	0.9461***	(0.0141)	0.9275***	(0.0247)	0.9289***	(0.0248)	0.9132**	(0.0387)	0.9150**	(0.0378)	0.9136**	(0.0374)
v_i^{sat}	satisfaction with																
	life (low)			1.0541	(0.1198)	1.0640	(0.1215)	0.8367	(0.1780)	0.8446	(0.1841)	0.6765	(0.2247)	0.6600	(0.2261)	0.6635	(0.2252)
	life (high)			1.4061***	(0.1625)	1.3972***	(0.1625)	1.3791	(0.2785)	1.3854	(0.2888)	1.1389	(0.3488)	1.1731	(0.3725)	1.1609	(0.3778)
	hh income (low)			0.8101*	(0.0933)	0.8047*	(0.0923)	1.0854	(0.2265)	1.0796	(0.2266)	1.0032	(0.3223)	1.0309	(0.3332)	1.0785	(0.3440)
	hh income (high)			0.7479*	(0.1135)	0.7547*	(0.1139)	0.7504	(0.1952)	0.7498	(0.1953)	1.0260	(0.3651)	1.0151	(0.3596)	0.9976	(0.3586)
	dwelling (low)			2.7050***	(0.2318)	2.7685***	(0.2383)	2.7643***	(0.4285)	2.7578***	(0.4292)	3.6037***	(0.8186)	3.4321***	(0.7819)	3.4645***	(0.7944)
	dwelling (high)			0.7972	(0.1168)	0.8063	(0.1193)	1.0488	(0.2586)	1.0324	(0.2590)	0.8700	(0.3304)	0.9383	(0.3622)	0.9721	(0.3817)
v_i^{mob}	previous moves					1.2180***	(0.0372)	1.2591***	(0.0631)	1.2543***	(0.0634)	1.2050**	(0.0880)	1.2035**	(0.0910)	1.2131**	(0.0919)
	covered distance					1.0003	(0.0002)	1.0007**	(0.0004)	1.0007*	(0.0004)	1.0000	(0.0006)	0.9998	(0.0007)	0.9998	(0.0006)
v_i^{pers}	risk attitude (low)					0.9721	(0.0939)	0.7902	(0.1366)	0.8339	(0.1473)	0.3720***	(0.1213)	0.3594***	(0.1175)	0.3810***	(0.1257)
	risk attitude (high)					1.1570	(0.1314)	1.0085	(0.2172)	0.9885	(0.2195)	1.0060	(0.2625)	1.0667	(0.2945)	1.0828	(0.2985)
	openness (low)									0.7968	(0.1581)			0.6343	(0.1997)	0.6442	(0.2032)
	openness (high)									1.1648	(0.1946)			0.8198	(0.2092)	0.8187	(0.2113)
	extraversion (low)									0.9338	(0.1814)			1.1023	(0.3084)	1.0713	(0.2988)
	extraversion (high)									1.0205	(0.1951)			0.9501	(0.2764)	0.9816	(0.2890)
	neuroticism (low)									0.8405	(0.1720)			1.0636	(0.3126)	1.0863	(0.3223)
	neuroticism (high)									1.1810	(0.2238)			1.6378*	(0.4479)	1.8482**	(0.5181)
	conscientiousness (low)									0.8352	(0.1570)			0.7604	(0.2161)	0.7690	(0.2201)
	conscientiousness (high)									1.0188	(0.2222)			0.8043	(0.2939)	0.8132	(0.3031)
	agreeableness (low)									0.8269	(0.1524)			0.9679	(0.2564)	1.0885	(0.2948)
	agreeableness (high)									0.8142	(0.1804)			0.7300	(0.2525)	0.7289	(0.2618)
	patience (low)															0.4963**	(0.1574)
	patience (high)															0.9018	(0.2798)
reference years		2008 - 2013		2008 - 2013		2008 - 2013		2009,2013		2009,2013		2013		2013		2013	
individuals		4044		4044		4044		2686		2686		1791		1791		1791	
individual-year observations		10793		10793		10793		3505		3505		1791		1791		1791	
LL(0)		-3111.58		-3111.58		-3111.58		-990.70		-990.70		-468.70		-468.70		-468.70	
LL		-2875.42		-2794.35		-2761.29		-863.84		-859.91		-396.56		-392.48		-389.75	
df		11		17		21		21		31		21		31		33	
Wald χ^2		400.50		531.66		623.05		226.12		238.89		129.93		137.88		148.69	
prob $> \chi^2$		0.0000		0.0000		0.0000		0.0000		0.0000		0.0000		0.0000		0.0000	
pseudo R-squared		0.0759		0.1020		0.1126		0.1281		0.1320		0.1539		0.1626		0.1684	
test H_0: coefficients in v_i are jointly zero		v_i^{lab}		v_i^{sat}, v_i^{lab}		v_i^{pers}	v_i^{mob}, v_i^{sat}, v_i^{lab}	v_i^{pers}	v_i^{pers}, v_i^{mob}, v_i^{sat}, v_i^{lab}	v_i^{pers}	v_i^{pers}, v_i^{mob}, v_i^{sat}, v_i^{lab}	v_i^{pers}	v_i^{pers}, v_i^{mob}, v_i^{sat}, v_i^{lab}	v_i^{pers}	v_i^{pers}, v_i^{mob}, v_i^{sat}, v_i^{lab}	v_i^{pers}	v_i^{pers}, v_i^{mob}, v_i^{sat}, v_i^{lab}
df (H_0)		3		9		2	13	2	13	12	23	2	13	12	23	14	25
Wald χ^2		20.46		179.22		1.88	245.83	1.94	99.05	9.50	107.14	9.43	61.68	15.93	67.67	24.39	76.40
prob $> \chi^2$		0.0001		0.0000		0.3905	0.0000	0.3797	0.0000	0.6598	0.0000	0.0090	0.0000	0.1943	0.000	0.0411	0.0000

*** p<0.01, ** p<0.05, * p<0.1

Note: Standard errors are clustered at the individual level. The pseudo R-squared is calculated as $1 - LL/LL(0)$.

Table A5.3: Residential moving likelihood – comparison of pooled and panel specifications

dependent variable		$y_{i,t+1}^{move}$ (residential move)													
sample		full sample				FE sample									
model		pooled OLS		RE		pooled OLS		FE		RE		Hausman test		test on coefficient equality	
		coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	β_{FE}	s.e.	β_{RE}	s.e.	$\beta_{FE}-\beta_{RE}$	s.e.	$\chi^2(1)$	p-value
v_i^{soc}	gender (female=1)	0.2971***	(0.0829)	0.2997***	(0.0837)										
	age (years)	-0.0383***	(0.0037)	-0.0388***	(0.0037)	-0.0199***	(0.0036)	1.4346***	(0.0872)	-0.0199***	(0.0044)	1.4545	(0.0871)	278.79	0.0000
	educational attainment														
	secondary	-0.0257	(0.1154)	-0.0269	(0.1122)										
	tertiary	-0.1185	(0.0952)	-0.1213	(0.0983)										
	number of kids in HH	-0.1266**	(0.0523)	-0.1287**	(0.0557)	-0.1524***	(0.0443)	-0.8014**	(0.4048)	-0.1524**	(0.0637)	-0.6491	(0.3998)	2.64	0.1045
	HH income	0.0000	(0.0000)	0.0000	(0.0000)	0.0001	(0.0001)	0.0003**	(0.0001)	0.0001	(0.0001)	0.0002	(0.0001)	3.62	0.0572
	partnership	0.0220	(0.0768)	0.0222	(0.0792)	-0.0611	(0.0880)	-0.4346**	(0.1984)	-0.0611	(0.0986)	-0.3735	(0.1722)	4.71	0.0300
	dwelling ownership	-0.8430***	(0.1384)	-0.8481***	(0.1388)	-0.0991	(0.1540)	-0.6913	(0.4464)	-0.0991	(0.1763)	-0.5922	(0.4101)	2.09	0.1487
v_i^{lab}	labour market participation														
	full-time	-0.4222***	(0.1042)	-0.4266***	(0.1074)	-0.1373	(0.1130)	0.3860	(0.3156)	-0.1373	(0.1359)	0.5233	(0.2848)	3.38	0.0662
	part-time	-0.1101	(0.1006)	-0.1124	(0.1017)	0.0116	(0.1103)	0.3662	(0.2641)	0.0116	(0.1276)	0.3546	(0.2312)	2.35	0.1251
	unempl. exp. (months)	-0.0555***	(0.0149)	-0.0557***	(0.0143)	0.0099	(0.0140)	0.2145	(0.1525)	0.0099	(0.0174)	0.2046	(0.1515)	1.82	0.1770
v_i^{sat}	satisfaction with														
	life low	0.0620	(0.1142)	0.0610	(0.1146)	0.0645	(0.1314)	0.2414	(0.2613)	0.0645	(0.1397)	0.1769	(0.2208)	0.64	0.4231
	life high	0.3345***	(0.1163)	0.3346***	(0.1188)	0.2190	(0.1471)	-0.0580	(0.2843)	0.2190	(0.1531)	-0.2770	(0.2395)	1.34	0.2475
	hh income low	-0.2173*	(0.1147)	-0.2202*	(0.1174)	-0.2326*	(0.1296)	0.2392	(0.2721)	-0.2326	(0.1464)	0.4718	(0.2293)	4.23	0.0396
	hh income high	-0.2814*	(0.1509)	-0.2874**	(0.1441)	-0.2676	(0.1783)	-0.6673**	(0.3183)	-0.2676	(0.1746)	-0.3998	(0.2662)	2.26	0.1331
	dwelling low	1.0183***	(0.0861)	1.0329***	(0.0881)	0.8399***	(0.1040)	1.0505***	(0.2021)	0.8398***	(0.1082)	0.2106	(0.1707)	1.52	0.2172
	dwelling high	-0.2153	(0.1480)	-0.2154	(0.1449)	-0.1118	(0.1719)	-0.2450	(0.3248)	-0.1118	(0.1753)	-0.1332	(0.2734)	0.24	0.6262
v_i^{mob}	previous moves	0.1972***	(0.0306)	0.1946***	(0.0294)	-0.1580***	(0.0391)	-6.1773***	(0.3264)	-0.1580***	(0.0360)	-6.0193	(0.3244)	344.34	0.0000
	covered distance	0.0003	(0.0002)	0.0003	(0.0002)	0.0001	(0.0002)	0.0048***	(0.0010)	0.0001	(0.0002)	0.0046	(0.0010)	22.92	0.0000
v_i^{pers}	risk attitude low	-0.0283	(0.0966)	-0.0287	(0.0996)	-0.0457	(0.1071)	-0.1424	(0.2433)	-0.0457	(0.1224)	-0.0967	(0.2102)	0.21	0.6455
	risk attitude high	0.1458	(0.1136)	0.1454	(0.1148)	0.1099	(0.1308)	0.1367	(0.2687)	0.1099	(0.1483)	0.0267	(0.2241)	0.01	0.9050
reference years		2008 – 2013		2008 – 2013		2008 – 2013		2008 – 2013		2008 – 2013					
individuals		4044		4044		601		601		601					
individual-year observations		10793		10793		2526		2526		2526					
log likelihood		-2761.29		-2761.09		-1458.82		-387.58		-1458.82					
df		21		21		18		18		18		18			
χ^2		623.05		559.96		124.69		994.40		112.59		364.55			
prob > χ^2		0.0000		0.0000		0.0000		0.0000		0.0000		0.0000			

*** p<0.01, ** p<0.05, * p<0.1

Note: The χ^2-statistic is a LR statistic in case of the fixed effects model (FE) and a Wald statistic in case of the random effects model (RE). Standard errors are clustered on the individual level in the pooled specifications, but not in the panel models to allow an application of the Hausman test. The Hausman test is based on a specification without those variables displaying insufficient variation over time to be used in a FE specification. In addition, the FE sample includes only those individuals for whom the dependent variable displays any variation over time. The resulting Hausman test statistic $\chi^2 = 364.55$ leads to a rejection of the Null of joint coefficient equality, thus the FE model is to be preferred. Tests on specific coefficient equality (last column) provide information on the factors likely to drive this outcome.

Table A5.4: Heterogeneous decisions in the distance space, conditional on moving

dependent variable		log(moving distance) $\mid y_{i,t+1}^{move} = 1$							
model		pooled OLS							
		(1)		(2)		(3)		(4)	
		coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.
v_i^{soc}	gender (female=1)	0.2367	(0.1789)	0.2354	(0.1790)	0.1826	(0.1768)	0.1668	(0.1768)
	age (years)	-0.0286***	(0.0071)	-0.0311***	(0.0071)	-0.0248***	(0.0070)	-0.0251***	(0.0071)
	educational attainment								
	(higher) vocational	-0.0536	(0.2485)	-0.0846	(0.2483)	-0.1227	(0.2464)	-0.1050	(0.2483)
	higher education	0.5671**	(0.2243)	0.5633**	(0.2227)	0.3316	(0.2241)	0.3281	(0.2280)
	number of kids in HH	-0.6139***	(0.1293)	-0.6258***	(0.1254)	-0.5592***	(0.1236)	-0.5559***	(0.1224)
	HH income	-0.0000	(0.0001)	0.0000	(0.0001)	0.0000	(0.0001)	0.0000	(0.0001)
	partnership	-0.1276	(0.1644)	-0.1075	(0.1669)	-0.0631	(0.1653)	-0.0611	(0.1650)
v_i^{lab}	labour market participation								
	full-time	-0.3215	(0.2334)	-0.2810	(0.2353)	-0.2222	(0.2347)	-0.2199	(0.2360)
	part-time	-0.0333	(0.2130)	0.0150	(0.2139)	0.0319	(0.2095)	0.0453	(0.2099)
	unempl. exp. (months)	-0.0565*	(0.0303)	-0.0760**	(0.0303)	-0.0755**	(0.0302)	-0.0795***	(0.0297)
v_i^{sat}	satisfaction with								
	life (low)			0.3884*	(0.2297)	0.4472*	(0.2283)	0.4413*	(0.2263)
	life (high)			0.0148	(0.2366)	-0.0501	(0.2358)	-0.1171	(0.2394)
	hh income (low)			0.4994*	(0.2725)	0.4787*	(0.2723)	0.4539*	(0.2714)
	hh income (high)			-0.0256	(0.2851)	-0.0859	(0.2805)	-0.0905	(0.2803)
v_i^{mob}	previous moves					-0.0312	(0.0553)	-0.0282	(0.0551)
	covered distance					0.0024***	(0.0005)	0.0024***	(0.0005)
v_i^{pers}	risk attitude (low)							0.3735*	(0.2046)
	risk attitude (high)							0.4158	(0.2568)
reference years		2008 – 2013		2008 – 2013		2008 – 2013		2008 – 2013	
individuals		776		776		776		776	
individual-year observations		907		907		907		907	
df		10		14		16		18	
F		6.30		5.63		6.50		6.10	
prob $> F$		0.0000		0.0000		0.0000		0.0000	
R-squared		0.0812		0.0911		0.1179		0.1234	
test H_0: coefficients in v_i are jointly zero		v_i^{lab}		v_i^{sat}	v_i^{sat}, v_i^{lab}	v_i^{mob}	$v_i^{sat}, v_i^{lab}, v_i^{mob}$	v_i^{pers}	$v_i^{sat}, v_i^{lab}, v_i^{mob}, v_i^{pers}$
df (H_0)		3		4	7	2	9	2	11
F		1.68		2.48	2.31	11.23	4.18	2.64	3.92
prob $> F$		0.1692		0.0426	0.0244	0.0000	0.0000	0.0719	0.0000

*** p<0.01, ** p<0.05, * p<0.1

Note: Standard errors are clustered at the individual level.

Table A5.5: Conditional logit results for heterogeneous selection probabilities in a high-dimensional destination space

dependent variable		$I(l_{t+1} \| y_{i,t+1}^{move}=1, z_{ilt})$															
		(1)		(1')		(2)		(2')		(3)		(3')		(4)		(4')	
		OR	s.e.	OR	s.e.	OR	s.e.	OR	s.e.	OR	s.e.	OR	s.e.	OR	s.e.	OR	s.e.
x_{il}	distance	0.9723***	(0.0017)	0.9724***	(0.0017)	0.9900*	(0.0054)	0.9901*	(0.0054)	0.9898*	(0.0052)	0.9900*	(0.0052)	0.9898**	(0.0052)	0.9899*	(0.0052)
x_l	population (in 1000)	1.0005***	(0.0001)	1.0005***	(0.0001)					1.0006***	(0.0001)	1.0005***	(0.0001)	1.0006***	(0.0001)	1.0005***	(0.0001)
	population density	1.0002	(0.0002)	1.0003	(0.0002)					1.0002	(0.0002)	1.0003	(0.0003)	1.0002	(0.0002)	1.0004	(0.0003)
	GDP per capita (1000 €)	0.9820*	(0.0106)	0.9837	(0.0106)					0.9732**	(0.0105)	0.9756**	(0.0105)	0.9735**	(0.0105)	0.9759**	(0.0105)
	share of recr. area	0.9692	(0.0279)	0.9770	(0.0285)					0.9807	(0.0303)	0.9892	(0.0306)	0.9827	(0.0305)	0.9912	(0.0307)
x_l^U	unemployment rate	1.0148	(0.0276)	1.0070	(0.0283)					1.0005	(0.0286)	0.9911	(0.0291)	1.0199	(0.0306)	1.0094	(0.0307)
x_l^{HS}	high-skilled emp. rate	1.0392*	(0.0223)	1.0403*	(0.0222)					1.0621***	(0.0239)	1.0606***	(0.0234)	1.0503**	(0.0247)	1.0492**	(0.0243)
$v_i^{soc}\#x_{il}$	gender (female=1)					1.0082**	(0.0035)	1.0080**	(0.0035)	1.0077**	(0.0034)	1.0077**	(0.0034)	1.0077**	(0.0034)	1.0077**	(0.0034)
	age (years)					0.9995***	(0.0001)	0.9995***	(0.0001)	0.9995***	(0.0001)	0.9995***	(0.0001)	0.9995***	(0.0001)	0.9995***	(0.0001)
	educational attainment																
	secondary					0.9934	(0.0052)	0.9935	(0.0051)	0.9931	(0.0051)	0.9933	(0.0051)	0.9932	(0.0051)	0.9933	(0.0051)
	tertiary					1.0115***	(0.0036)	1.0113***	(0.0036)	1.0115***	(0.0035)	1.0114***	(0.0035)	1.0114***	(0.0035)	1.0113***	(0.0035)
	number of kids in HH					0.9909*	(0.0051)	0.9909*	(0.0051)	0.9901*	(0.0053)	0.9901*	(0.0053)	0.9902*	(0.0053)	0.9902*	(0.0053)
	HH income					1.0000	(0.0000)	1.0000	(0.0000)	1.0000	(0.0000)	1.0000	(0.0000)	1.0000	(0.0000)	1.0000	(0.0000)
	partnership					0.9957*	(0.0025)	0.9958*	(0.0024)	0.9963	(0.0024)	0.9962	(0.0024)	0.9963	(0.0024)	0.9962	(0.0023)
$v_i^{soc}\#x_{il}$	LM participation																
	full-time					0.9977	(0.0038)	0.9976	(0.0038)	0.9976	(0.0036)	0.9976	(0.0036)	0.9976	(0.0036)	0.9976	(0.0036)
	part-time					0.9982	(0.0033)	0.9985	(0.0033)	0.9984	(0.0032)	0.9986	(0.0032)	0.9984	(0.0032)	0.9986	(0.0032)
	unemp. experience					0.9988	(0.0007)	0.9988	(0.0007)	0.9988	(0.0008)	0.9987	(0.0008)	0.9988	(0.0008)	0.9987*	(0.0008)
$v_i^{sat}\#x_{il}$	satisfaction with																
	life (low)					1.0066*	(0.0040)	1.0065	(0.0040)	1.0064*	(0.0038)	1.0063	(0.0038)	1.0063	(0.0039)	1.0062	(0.0039)
	life (high)					0.9951	(0.0032)	0.9951	(0.0032)	0.9954	(0.0031)	0.9954	(0.0031)	0.9953	(0.0031)	0.9953	(0.0031)
	HH income (low)					1.0039	(0.0040)	1.0039	(0.0040)	1.0044	(0.0038)	1.0045	(0.0038)	1.0045	(0.0038)	1.0046	(0.0038)
	HH income (high)					0.9951	(0.0050)	0.9952	(0.0052)	0.9956	(0.0049)	0.9956	(0.0051)	0.9954	(0.0048)	0.9955	(0.0049)
$v_i^{mob}\#x_{il}$	sum of res. moves					0.9958***	(0.0013)	0.9958***	(0.0013)	0.9960***	(0.0013)	0.9960***	(0.0013)	0.9960***	(0.0013)	0.9960***	(0.0013)
	sum of covered distance					1.0000***	(0.0000)	1.0000***	(0.0000)	1.0000***	(0.0000)	1.0000***	(0.0000)	1.0000***	(0.0000)	1.0000***	(0.0000)
$v_i^{pers}\#x_{il}$	risk attitude (low)					1.0019	(0.0036)	1.0021	(0.0036)	1.0019	(0.0035)	1.0021	(0.0035)	1.0020	(0.0036)	1.0022	(0.0036)
	risk attitude (high)					1.0056*	(0.0031)	1.0055*	(0.0031)	1.0057*	(0.0029)	1.0057*	(0.0029)	1.0057*	(0.0030)	1.0056*	(0.0030)
$v_i^{pers}\#x_l^U$	risk attitude (low)													0.8947**	(0.0480)	0.8957**	(0.0479)
	risk attitude (high)													0.9903	(0.0545)	0.9956	(0.0548)
$v_i^{pers}\#x_l^{HS}$	risk attitude (low)													1.0468	(0.0344)	1.0459	(0.0338)
	risk attitude (high)													1.0143	(0.0339)	1.0137	(0.0334)
information-processing control				✓				✓				✓				✓	
reference years		2008 – 2013		2008 – 2013		2008 – 2013		2008 – 2013		2008 – 2013		2008 – 2013		2008 – 2013		2008 – 2013	
individuals		679		679		679		679		679		679		679		679	
individual-year observations $\times D$		75936		75936		75936		75936		75936		75936		75936		75936	
$LL(0)$		-3689.58		-3689.58		-3689.58		-3689.58		-3689.58		-3689.58		-3689.58		-3689.58	
log pseudolikelihood (LL)		-1685.75		-1681.81		-1525.20		-1515.26		-1468.30		-1463.53		-1465.98		-1461.24	
df		7		8		19		20		25		26		29		30	
Wald χ^2		514.84		529.27		391.23		405.84		563.11		578.63		586.52		606.97	
prob $> \chi^2$		0.0000		0.0000		0.0000		0.0000		0.0000		0.0000		0.0000		0.0000	
pseudo R-squared $(1-LL/LL(0))$		0.5431		0.5442		0.5866		0.5893		0.6020		0.6033		0.6027		0.6040	
test H_0: coefficients in z_{ik} are jointly zero		x_{il}	x_l	x_{il}	x_l	x_{il}	$v_i\#x_{li}$	x_{il}	$v_i\#x_{li}$	x_l	$v_i\#x_{li}$	x_l	$v_i\#x_{li}$	x_l	$v_i\#x_{li}$, $v_i\#x_l$	x_l	$v_i\#x_{li}$, $v_i\#x_l$
df (H_0)		1	6	1	6	1	18	1	18	6	18	6	18	6	22	6	22
Wald χ^2		271.38	128.18	267.32	116.81	3.44	130.14	3.34	131.30	132.61	131.62	122.09	133.45	113.96	137.63	99.29	140.05
prob $> \chi^2$		0.0000	0.0000	0.0000	0.0000	0.0636	0.0000	0.0675	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

*** p<0.01, ** p<0.05, * p<0.1

Note: Distance refers to the distance between the centroid of the current residence's RPU and the centroid of a potential destination RPU. All individual level variables, constant across potential destinations, are interacted with the respective distance x_{il} or a destination-specific variable x_l. Standard errors are clustered at the individual level. The information processing control corresponds to the accessibility measure, addressing varying degrees of substitutability of alternatives which may lead to a violation of the 'independence from irrelevant alternatives' (IIA) assumption in the random utility framework.

Figure A6.1: Items for expected income levels under various scenarios

5.1 **What would be the <u>minimum monthly net income</u>* you expect to receive after you eventually will have graduated from university?**

*(*corresponds to the income after taxes and social insurance contributions have been deducted)*

____________________ Euro

5.3 **Imagine, that after graduation, you will receive an interesting job offer in the vicinity of your current residence, realising the monthly net income you expect** (see Question 5.1).

What would be the <u>minimum</u> monthly net income for an otherwise comparable job offer, which made you willing to move for this alternative job to an unfamilar environment:

to another state ____________________ Euro per month (net)

to another country ____________________ Euro per month (net)

5.6 **Imagine, that despite intensive job search after graduation, you will <u>NOT</u> receive an interesting job offer in the vicinity of your current residence, realising the monthly net income you expect** (see Question 5.1).

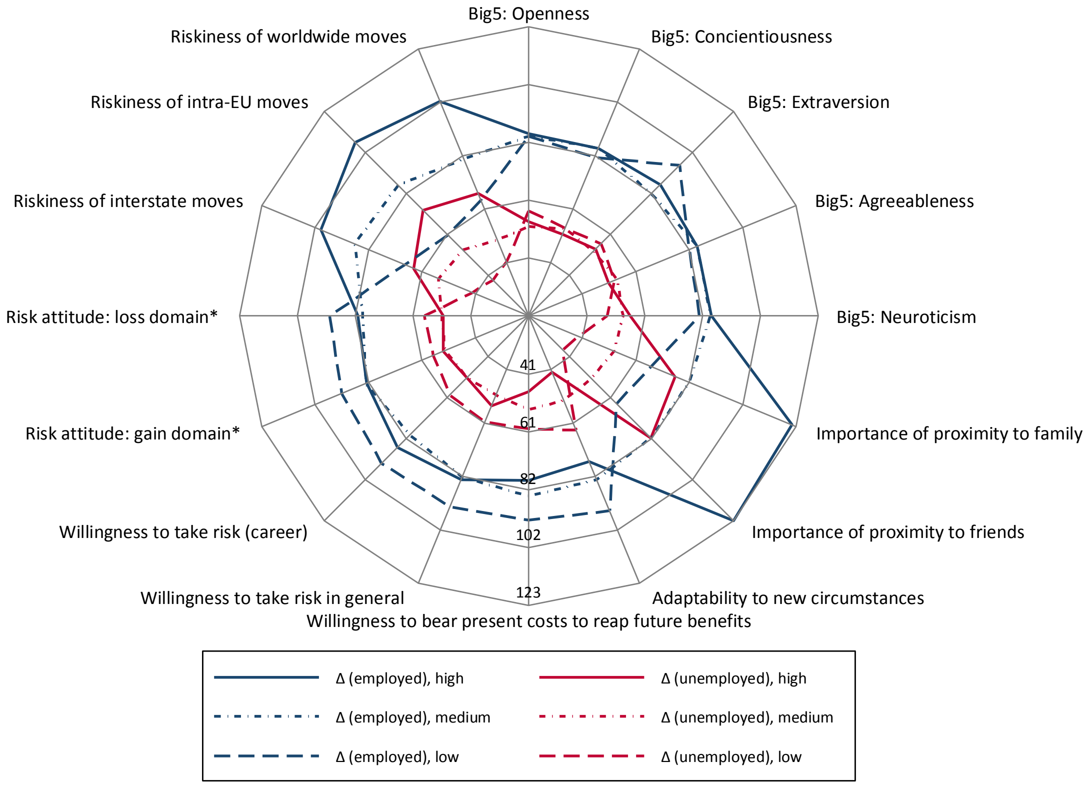
What would be the <u>minimum</u> monthly net income for a job offer you were interested in, which made you willing to move for this alternative job to an unfamilar environment:

to another state ____________________ Euro per month (net)

to another country ____________________ Euro per month (net)

Note: Depicted items are translated versions from the German original. Their visual presentation corresponds exactly to the layout the original items had in the MESARS-survey. Item 5.1 gives the reference income, labelled w_O. In the scenarios with existing job alternative the first answer of question 5.3 corresponds to w_{A1}, the second one to w_{A2}. Similarly, the first answer to question 5.6 yields w_{U1}, the second w_{U2} in the unemployment scenarios.

Figure A6.2: Mobility premiums for cross-border migration scenarios, conditional on personality groupings (in %)



Note: * The solid line represents risk-loving individuals; the line with dashes and dots stands for risk-neutral and the dashed-line for risk-averse individuals. In all other cases, the three depicted groups refer to a classification based on standardised scores, such that 'medium' refers to those scoring within one standard deviation around the mean and 'high' ('low') comprises those more than one standard deviation above (below) the mean. The sample size varies across dimensions between 2096 and 2172.

Table A6.1: Assumed interrelationships between the mobility premium, basic model components and personality parameters

model parameter m	description	$\frac{\partial\Delta}{\partial m}$	personality / preference parameter b	description	$\frac{\partial m}{\partial b}$
p_D	price level at destination	$\frac{\partial\Delta}{\partial p_D} > 0$			
p_O	price level at origin	$\frac{\partial\Delta}{\partial p_O} < 0$			
a_D	amenity level at destination	$\frac{\partial\Delta}{\partial a_D} < 0$			
a_O	amenity level at origin	$\frac{\partial\Delta}{\partial a_O} > 0$			
η_D	unemployment insurance replacement rate at destination	$\frac{\partial\Delta}{\partial \eta_D} < 0$			
η_O	unemployment insurance replacement rate at origin	$\frac{\partial\Delta}{\partial \eta_O} > 0$			
Γ_D	fixed costs of moving	$\frac{\partial\Delta}{\partial \Gamma_D} > 0$			
w_O	accustomed wage income at origin	$\frac{\partial\Delta}{\partial w_O} < 0$			
$\gamma_i(\phi_A, \psi_O, d, \chi, \Lambda_L)$	individual adjustment capability	$\frac{\partial\Delta}{\partial \gamma_i} < 0$	ϕ_A	adaptability to new circumstances	$\frac{\partial\gamma_i(\phi_A,\psi_O,d,\chi,\Lambda_L)}{\partial\phi_A} > 0$
			χ	previous mobility experiences (internal or abroad)	$\frac{\partial\gamma_i(\phi_A,\psi_O,d,\chi,\Lambda_L)}{\partial\psi_O} > 0$
			Λ_L	local language proficiency	$\frac{\partial\gamma_i(\phi_A,\psi_O,d,\chi,\Lambda_L)}{\partial\Lambda_L} > 0$
			ψ_O	Big-Five: openness to new experiences	$\frac{\partial\gamma_i(\phi_A,\psi_O,d,\chi,\Lambda_L)}{\partial\psi_O} > 0$
			d	moving distance / cross-border versus internal move	$\frac{\partial\gamma_i(\phi_A,\psi_O,d,\chi,\Lambda_L)}{\partial d} < 0$
$\tau_i(\psi_E, \phi_S)$	psychic cost parameter	$\frac{\partial\Delta}{\partial \tau_i} > 0$	ψ_E	Big-Five: extraversion	$\frac{\partial\tau_i(\psi_E,\phi_S)}{\partial\psi_E} < 0$
			ϕ_S	social preferences: proximity to reference persons	$\frac{\partial\tau_i(\psi_E,\phi_S)}{\partial\phi_S} > 0$
$\pi_{UO,i}(\pi_{UO}, \psi_N)$	perceived probability of job loss at origin, also depending on objective local unemployment risk π_{UO}	$\frac{\partial\Delta}{\partial \pi_{UO,i}} < 0$	ψ_N	Big-Five: neuroticism	$\frac{\partial\pi_{UO,i}(\psi_N)}{\partial\psi_N} > 0$
$\pi_{EL,i}(\psi_C, \psi_A, \phi_R, \phi_P, \Lambda_L)$	job finding probability at location L (depends also on objective local conditions π_{ED} and π_{EO})	$\frac{\partial\Delta}{\partial \pi_{EO,i}} > 0$ $\frac{\partial\Delta}{\partial \pi_{ED,i}} \lesseqgtr 0$	ψ_C	Big-Five: conscientiousness	$\frac{\partial\pi_{EL,i}(\psi_C,\psi_A,\phi_R,\phi_P,\Lambda_L)}{\partial\psi_C} > 0$
			ψ_A	Big-Five: agreeableness	$\frac{\partial\pi_{EL,i}(\psi_C,\psi_A,\phi_R,\phi_P,\Lambda_L)}{\partial\psi_A} > 0$
			ϕ_R	risk attitude	$\frac{\partial\pi_{EL,i}(\psi_C,\psi_A,\phi_R,\phi_P,\Lambda_L)}{\partial\phi_R} > 0$
			ϕ_P	patience parameter	$\frac{\partial\pi_{EL,i}(\psi_C,\psi_A,\phi_R,\phi_P,\Lambda_L)}{\partial\phi_P} > 0$
			Λ_L	local language skill	$\frac{\partial\pi_{EL,i}(\psi_C,\psi_A,\phi_R,\phi_P,\Lambda_L)}{\partial\Lambda_L} > 0$

Table A6.2: Overall descriptive statistics for model variables included in the empirical analyses

category		variable label	short description	original scale	N	min	max	mean	std.dev.	modified scale
mobility premiums	Δ_{A1}	*internal, given job alternative*	dependent variable	cardinal	1851	-71.43	185.71	27.016	25.80	
	Δ_{U1}	*internal, given unemployment*	dependent variable	cardinal	1851	-71.43	150	6.65	28.04	
	Δ_{A2}	*cross-border, given job alternative*	dependent variable	cardinal	1851	-42.86	900	82.60	75.62	
	Δ_{U2}	*cross-border, given unemployment*	dependent variable	cardinal	1851	-66.67	525	52.64	66.68	
socio-demographic	X	*gender*	1: female, 0: male	binary	1851	0	1	0.42	/	
		age	age in years	cardinal	1851	17	49	20.28	2.35	
		partnership	1: currently in a relationship, 0: no relationship	binary	1851	0	1	0.44	/	
	Λ	*English language proficiency*	(1: mother tongue or business fluent, 2: fluent in daily routine, 3: basic	ordinal	1851	1	3	/	/	
Big-Five / personality	ϕ_R	*risk attitude (career domain)*	willingness to take risk, 11-point scale (1: low, 11: high)	ordinal	1851	1	11	5.54	2.49	✓
	ϕ_P	*patience*	willingness to bear costs in the present for future benefits, 7-point scale (1: low, 7: high)	ordinal	1851	1	7	5.46	1.16	✓
	ψ_E	*extraversion*	5-point scale (1: low, 5: high)	ordinal	1851	1	5	3.42	0.96	✓
	ψ_N	*neuroticism*	5-point scale (1: low, 5: high)	ordinal	1851	1	5	2.82	0.92	✓
	ψ_O	*openness*	5-point scale (1: low, 5: high)	ordinal	1851	1	5	3.24	1.03	✓
	ψ_C	*conscientiousness*	5-point scale (1: low, 5: high)	ordinal	1851	1	5	3.37	0.90	✓
	ψ_A	*agreeableness*	5-point scale (1: low, 5: high)	ordinal	1851	1	5	2.95	0.81	✓
	ϕ_A	*adaptability*	ability to adapt to new circumstances, 7-point scale (1: low, 7: high)	ordinal	1851	1	7	3.97	1.52	✓
social preference	ϕ_S	*importance of proximity (family)*	7-point scale (1: low, 7: high)	ordinal	1851	1	7	4.75	1.64	✓
	ϕ_S	*importance of proximity (friends)*	7-point scale (1: low, 7: high)	ordinal	1851	1	7	5.00	1.44	✓
perceived behavioural control	θ_{R1}	*riskiness of moving to another state*	7-point scale (1: not at all risky, 7: risky)	ordinal	1851	1	7	2.83	1.62	✓
	θ_{R2}	*riskiness of moving to another Europ. country*	7-point scale (1: not at all risky, 7: risky)	ordinal	1850	1	7	4.41	1.66	✓
migration intentions	θ_{M1}	*moving to another state*	7-point scale (1: highly unlikely, 7: highly likely)	ordinal	1848	1	7	4.96	1.69	✓
	θ_{M2}	*moving to another European country*	7-point scale (1: highly unlikely, 7: highly likely)	ordinal	1850	1	7	3.16	1.65	✓
labour market readiness		*work experience*	2: fulltime, 1: part-time or mini-job, 0: none	ordinal	1850	0	2	/	/	
		vocational training	1: vocational training completed, 0: otherwise	binary	1848	0	1	0.17	/	
		master student	1: master student, 0 : bachelor student	binary	1850	0	1	0.02	/	
previous mobility experiences	χ	*residential move during school*	1: at least one residential move during school, 0: none	binary	1851	0	1	0.23	/	
	χ	*exchange participation*	1 : exchange participation during school, 0 : otherwise	binary	1851	0	1	0.33	/	
	χ	*stay abroad*	1 : at least one month abroad without family, 0: otherwise	binary	1851	0	1	0.23	/	
	χ	*educational mobility*	excess distance of chosen university	km, cardinal	1851	0	531.2	89.36	107.79	
local conditions at origin	a_O	*GDP (per capita)*	INKAR 2012 data	cardinal, 1000 €	1851	16.5	106.2	33.38	10.71	
	p_O/a_O	*price level / building prices*	proxied by local building plot prices	cardinal, € per m^2	1851	16	368.4	130.77	80.80	
	a_O	*accessibility of 3 closest agglomeration centres by train*	aggregated travel time to the three nearest agglomeration centres; INKAR 2012 data	minutes, cardinal	1851	36	181	83.39	25.44	
	a_O	*accessibility of 3 closest agglomeration centres by car*	aggregated travel time to the three nearest agglomeration centres; INKAR 2012 data	minutes, cardinal	1851	44	151	90.57	14.20	
	a_O	*population density*	INKAR 2012 data	cardinal	1851	58.6	3005.9	970.32	669.32	
	a_O	*recreational area (per capita)*	INKAR 2012 data	cardinal, m^2	1851	17	333.8	75.09	62.07	
	a_O	*public service provision*	public employees (full time equivalents) per 10000 inhabitants; INKAR 2012 data	cardinal	1851	56.3	269.1	168.11	40.38	
	π_{UO}	*unemployment rate*	INKAR 2012 data	%	1851	3.1	14.3	9.37	2.91	
other	w_O	expected monthly net income	expected post-graduation income net income tax and social insurance contributions	log	1851	5.86	10.71	7.92	0.44	

Note: Overall descriptive statistics (for other variables than the mobility premiums) are conditional on the existence of all four scenario specific mobility premiums and refer to the preferred specification. 'Original scale' refers to the scale the information has been elicited from survey participants. Modified variables have been standardised and categorised into three distinct groups: those scoring low (score below the mean minus one standard deviation), the reference group of medium-type individuals (score within the range of one standard deviation around the mean) and those scoring high (score more than one standard deviation above the mean). Standard deviations are only reported for cardinal variables. INKAR data originates from the INKAR online database (BBSR, 2014).

Table A6.3: OLS model comparison for pooled mobility premiums

dependent variable		Δ (pooled)															
estimation method		OLS															
		coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.
gender (female=1)		-0.4960	(1.2364)	-0.5368	(1.2238)	-1.1617	(1.3610)	-1.3941	(1.3556)	-2.9363**	(1.3719)	0.3680	(1.3587)	-1.4270	(1.3706)	-0.4406	(1.3801)
age		-0.1228	(0.3267)	-0.2396	(0.3204)	-0.1124	(0.3224)	-0.0609	(0.3186)	-0.1742	(0.3170)	0.0993	(0.3163)	0.0132	(0.3135)	0.1976	(0.3096)
partnership (yes=1)		5.9548***	(1.2439)	5.7206***	(1.2401)	5.9233***	(1.2503)	5.7708***	(1.2458)	4.9327***	(1.2267)	5.3391***	(1.2391)	4.5258***	(1.2187)	4.5730***	(1.2259)
language skills (English)																	
	high	-11.9575***	(2.1235)	-12.0859***	(2.1325)	-11.2107***	(2.1557)	-10.3761***	(2.1524)	-9.5596***	(2.1582)	-6.4409***	(2.1708)	-5.4846**	(2.1700)	-5.8999***	(2.1750)
	medium	-5.2754**	(2.0899)	-5.5349***	(2.0775)	-5.4370***	(2.0925)	-5.6901***	(2.0885)	-5.6032***	(2.0878)	-3.5606*	(2.0624)	-3.8161*	(2.0635)	-3.6926*	(2.0665)
risk attitude	score $< \mu - \sigma$					6.3095***	(1.5167)	6.1467***	(1.5109)	4.2975***	(1.4937)	4.9601***	(1.4991)	3.2169**	(1.4854)	2.8567*	(1.4944)
(career domain)	score $> \mu + \sigma$					0.6999	(2.0845)	0.9463	(2.0673)	1.3860	(2.0384)	1.6560	(2.0718)	1.9471	(2.0277)	1.5061	(2.0309)
patience	score $< \mu - \sigma$					5.1266***	(1.8634)	5.5062***	(1.8727)	5.6494***	(1.8591)	5.2702***	(1.8458)	5.5332***	(1.8439)	5.6116***	(1.8501)
	score $> \mu + \sigma$					-4.1372**	(1.6282)	-2.9646*	(1.6958)	-3.0686*	(1.6793)	-3.2979**	(1.6100)	-2.9838*	(1.6646)	-3.3502**	(1.6726)
extraversion	score $< \mu - \sigma$					3.4437	(2.1725)	0.7065	(2.1494)	0.0803	(2.1414)	2.2634	(2.1757)	-0.5623	(2.1348)	-0.0218	(2.1419)
	score $> \mu + \sigma$					0.8463	(1.6163)	2.4783	(1.6145)	1.5619	(1.6024)	1.6280	(1.5962)	1.7294	(1.5828)	1.5527	(1.5872)
neuroticism	score $< \mu - \sigma$					-1.3459	(2.1409)	0.6673	(2.1160)	0.0441	(2.1265)	-1.1377	(2.1380)	-0.2922	(2.1250)	-1.4790	(2.1270)
	score $> \mu + \sigma$					-0.2557	(1.6629)	-1.5522	(1.6657)	-1.1106	(1.6463)	0.1586	(1.6462)	-0.5316	(1.6377)	-0.6733	(1.6478)
openness	score $< \mu - \sigma$					-0.7483	(1.6507)	-1.1746	(1.6354)	-2.1639	(1.6208)	-1.0395	(1.6464)	-2.2346	(1.6215)	-1.8984	(1.6304)
	score $> \mu + \sigma$					-0.4221	(1.6728)	0.0689	(1.6740)	-0.2008	(1.6443)	-0.5494	(1.6553)	-0.4738	(1.6307)	-0.0339	(1.6550)
conscientious-	score $< \mu - \sigma$					0.0971	(2.1183)	-0.2934	(2.0958)	-0.7387	(2.0753)	0.7664	(2.0995)	-0.1602	(2.0614)	-0.1909	(2.0655)
ness	score $> \mu + \sigma$					-1.0358	(1.6083)	-0.7741	(1.6056)	-1.1560	(1.5884)	-1.9005	(1.6048)	-2.0733	(1.5892)	-2.6220	(1.6000)
agreeableness	score $< \mu - \sigma$					0.0052	(1.6310)	-0.3282	(1.6276)	1.2779	(1.6118)	-0.8038	(1.6166)	0.4499	(1.6026)	0.1470	(1.6072)
	score $> \mu + \sigma$					1.0281	(1.6464)	1.3174	(1.6457)	1.0775	(1.6143)	1.7835	(1.6132)	1.6450	(1.5898)	2.5584	(1.5997)
adaptability	score $< \mu - \sigma$							9.7682***	(1.7109)	7.3282***	(1.6799)			6.4159***	(1.6698)	6.1156***	(1.6800)
	score $> \mu + \sigma$							-7.0430***	(1.8236)	-4.0675**	(1.8317)			-0.8650	(1.8667)	-0.8567	(1.8749)
importance of	score $< \mu - \sigma$									-3.5237**	(1.6194)			-2.9647*	(1.6278)	-2.5849	(1.6315)
prox. (family)	score $> \mu + \sigma$									9.5592***	(2.1529)			9.6209***	(2.1239)	9.3428***	(2.1294)
importance of	score $< \mu - \sigma$									-7.2379***	(1.7131)			-6.7878***	(1.6812)	-7.2649***	(1.6843)
prox. (friends)	score $> \mu + \sigma$									11.5480***	(2.3336)			10.4159***	(2.3144)	11.4089***	(2.3165)
previous mobility experiences (χ)																	
	residential move (yes=1)											-0.4114	(1.4416)	0.7753	(1.4290)	1.1933	(1.4429)
	exchange participation (yes=1)											-4.5267***	(1.2957)	-3.8862***	(1.2788)	-3.9259***	(1.2874)
	stay abroad (yes=1)											-11.6974***	(1.3962)	-10.7625***	(1.3930)	-10.5340***	(1.3988)
	educational mobility (km)											-0.0455***	(0.0058)	-0.0370***	(0.0060)	-0.0398***	(0.0060)
local conditions at origin (a_O)																	
	GDP (per capita)			-1.0309***	(0.2120)	-0.9937***	(0.2145)	-1.0053***	(0.2146)	-0.9617***	(0.2120)	-0.9161***	(0.2085)	-0.8941***	(0.2075)	-0.8472***	(0.2085)
	building land prices			0.1140***	(0.0316)	0.1164***	(0.0318)	0.1190***	(0.0318)	0.1049***	(0.0316)	0.0988***	(0.0311)	0.0915***	(0.0311)	0.0867***	(0.0312)
	accessibility (train)			-0.1961***	(0.0531)	-0.1976***	(0.0536)	-0.2192***	(0.0538)	-0.1940***	(0.0533)	-0.2037***	(0.0526)	-0.1950***	(0.0525)	-0.2000***	(0.0525)
	accessibility (car)			0.0469	(0.1039)	0.0581	(0.1047)	0.0845	(0.1046)	0.0225	(0.1040)	0.1007	(0.1030)	0.0547	(0.1028)	0.0656	(0.1028)
	pop. density			-0.0022	(0.0023)	-0.0024	(0.0023)	-0.0020	(0.0023)	-0.0028	(0.0023)	-0.0012	(0.0023)	-0.0018	(0.0023)	-0.0017	(0.0023)
	recreational area (per capita)			0.0412	(0.0277)	0.0463*	(0.0277)	0.0571**	(0.0276)	0.0464*	(0.0276)	0.0638**	(0.0274)	0.0600**	(0.0274)	0.0616**	(0.0275)
	public services			-0.0352	(0.0475)	-0.0379	(0.0475)	-0.0414	(0.0473)	-0.0179	(0.0469)	0.0079	(0.0471)	0.0184	(0.0467)	0.0152	(0.0471)
	unemployment rate (π_{UO})			-1.8517***	(0.6726)	-1.7632***	(0.6719)	-1.7740***	(0.6712)	-1.6242**	(0.6654)	-1.8515***	(0.6637)	-1.7269***	(0.6611)	-1.6374**	(0.6616)
premium type controls		✓		✓		✓		✓		✓		✓		✓		✓	
relative income control (w_0)		✓		✓		✓		✓		✓		✓		✓			
constant		✓		✓		✓		✓		✓		✓		✓		✓	
observations		7404		7404		7404		7404		7404		7404		7404		7404	
df (model)		9		17		31		33		37		35		41		40	
F-statistic		253.61		139.83		79.05		74.28		67.44		70.21		61.11		62.45	
prob > F		0.0000		0.0000		0.0000		0.0000		0.0000		0.0000		0.0000		0.0000	
R-squared		0.2347		0.2425		0.2469		0.2527		0.2686		0.2628		0.2800		0.2728	
adjusted R-squared		0.2337		0.2408		0.2437		0.2494		0.2649		0.2593		0.2760		0.2689	

*** p<0.01, ** p<0.05, * p<0.1

Note: Heteroscedasticity robust standard errors are implemented.

Table A6.4: Quantile regression model comparison for pooled mobility premiums

dependent variable		Δ (pooled)																
estimation method		QREG ($q = 0.25$)		QREG ($q = 0.50$)		QREG ($q = 0.75$)		QREG ($q = 0.25$)		QREG ($q = 0.50$)		QREG ($q = 0.75$)		QREG ($q = 0.25$)		QREG ($q = 0.50$)		QREG ($q = 0.75$)	
		coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.
gender (female=1)		-0.9815	(0.9771)	-0.5515	(0.9557)	-0.5584	(1.4618)	-1.6330*	(0.9168)	-1.4717	(0.9788)	-3.6496**	(1.4396)	0.2119	(0.8382)	0.1200	(0.8979)	1.0220	(1.4263)
age		0.1619	(0.1827)	0.1604	(0.2008)	-0.0249	(0.2822)	0.1301	(0.2001)	0.0226	(0.1874)	-0.3171	(0.2928)	0.4797***	(0.1635)	0.4421**	(0.2006)	-0.2120	(0.2816)
partnership (yes=1)		4.2207***	(0.8875)	4.2973***	(0.8329)	4.5766***	(1.3621)	3.4344***	(0.8093)	3.6120***	(0.8014)	3.2657***	(1.2554)	3.0872***	(0.8064)	4.8000***	(0.8508)	4.1488***	(1.2356)
language skills (English)																			
	high	-4.4753***	(1.3406)	-5.1173***	(1.3596)	-6.1428***	(2.1124)	-3.2286**	(1.5868)	-3.7065**	(1.4481)	-5.0891***	(1.8623)	-2.3958*	(1.2295)	-2.7605*	(1.4997)	-2.6939	(2.2020)
	medium	-1.8285	(1.2421)	-2.4628*	(1.3027)	-3.4723*	(1.9506)	-1.1414	(1.3782)	-1.8686	(1.3235)	-3.9835**	(1.7222)	-1.5094	(1.1670)	-1.7701	(1.3391)	-2.1005	(2.0478)
risk attitude	score $< \mu - \sigma$	1.4131	(1.0265)	3.6614***	(1.0757)	5.6479***	(1.5629)	1.2226	(0.9989)	1.5667	(1.0172)	3.5229**	(1.4403)	0.8019	(0.8456)	2.5431**	(0.9963)	4.8466***	(1.6817)
(career domain)	score $> \mu + \sigma$	-2.9253**	(1.4434)	-0.1773	(1.1798)	2.3527	(1.9012)	-1.8408	(1.4022)	0.3949	(1.3589)	1.9355	(1.9097)	-1.7216	(1.2915)	-1.0547	(1.4504)	2.7690	(1.9012)
patience	score $< \mu - \sigma$	0.5523	(1.1805)	1.1561	(1.2269)	4.7769**	(1.9924)	0.6833	(1.2456)	1.0713	(1.3171)	5.7046***	(1.6846)	0.7323	(1.1038)	1.4290	(1.2930)	4.9105**	(1.9403)
	score $> \mu + \sigma$	-3.4023***	(1.1619)	-1.6621	(1.1287)	-2.9984*	(1.5378)	-2.3278*	(1.3841)	-0.4001	(1.1832)	-1.3698	(1.5567)	-2.3001*	(1.3149)	-1.8285	(1.2086)	-0.8056	(1.5482)
extraversion	score $< \mu - \sigma$	0.0172	(1.4492)	-0.0005	(1.4675)	2.0223	(2.1141)	-1.3230	(1.3362)	-0.8845	(1.4336)	-2.2313	(2.0428)	-0.7703	(1.2221)	-1.0268	(1.3905)	1.1062	(2.2971)
	score $> \mu + \sigma$	-2.3363**	(1.1484)	-0.7389	(1.0232)	2.7709	(1.7101)	-1.9360*	(1.1523)	0.1298	(1.2110)	3.5349**	(1.5853)	-0.9742	(0.9605)	0.3884	(1.1199)	2.0028	(1.6168)
neuroticism	score $< \mu - \sigma$	-1.9921	(1.3797)	-2.2281*	(1.2159)	-5.1931***	(1.6705)	-1.4619	(1.2716)	-1.8797	(1.3561)	-4.1045**	(1.9808)	-2.6529**	(1.2780)	-2.5320**	(1.2252)	-5.1563***	(1.7704)
	score $> \mu + \sigma$	1.3589	(1.1840)	0.0213	(1.2488)	-0.7306	(1.6240)	0.9705	(1.1966)	-0.0389	(1.2871)	-0.5725	(1.8551)	1.3777	(1.0751)	-0.2035	(1.1837)	-0.6050	(1.9721)
openness	score $< \mu - \sigma$	-1.2555	(1.0095)	-2.1946**	(1.0670)	-2.2678	(1.5418)	-1.9740*	(1.1036)	-2.0150*	(1.0990)	-2.0538	(1.4835)	-1.4191	(0.9185)	-3.3357***	(1.1314)	-1.6028	(1.6727)
	score $> \mu + \sigma$	-1.6994	(1.1858)	-1.8453*	(0.9648)	-0.1531	(1.6757)	-1.9409	(1.1899)	-1.7363	(1.1619)	-0.4171	(1.7221)	-1.5517	(0.9996)	-3.1581***	(1.0902)	0.1645	(1.5933)
conscientious-	score $< \mu - \sigma$	-3.8636***	(1.4069)	-0.4130	(1.3873)	1.8132	(2.0778)	-2.4465	(1.7758)	-0.5535	(1.3957)	-0.0630	(1.9972)	-2.4180*	(1.4496)	0.0894	(1.4315)	0.4814	(1.9925)
ness	score $> \mu + \sigma$	-0.9059	(1.1886)	0.6509	(1.0975)	0.7807	(1.7047)	-0.5195	(1.2424)	0.3631	(1.1053)	2.6568	(1.7966)	-0.8479	(1.2404)	0.1856	(1.2837)	0.8715	(1.6471)
agreeableness	score $< \mu - \sigma$	-0.5309	(0.9624)	-0.8934	(1.0266)	-1.1436	(1.5791)	-0.0821	(1.0633)	-0.6131	(1.0949)	0.9131	(1.6684)	-1.5566*	(0.9362)	-1.3372	(1.1700)	-1.6902	(1.6645)
	score $> \mu + \sigma$	2.3140*	(1.3540)	1.7968*	(1.0852)	3.8698**	(1.7631)	1.7608	(1.2572)	2.4010**	(1.1926)	3.0186*	(1.7583)	2.5169**	(1.0660)	2.2914**	(1.1528)	3.2181*	(1.6946)
adaptability	score $< \mu - \sigma$							2.5495**	(1.1861)	3.6185***	(1.1195)	7.3649***	(1.9653)						
	score $> \mu + \sigma$							-2.4117*	(1.2819)	-2.4326*	(1.3955)	-3.8554**	(1.7560)						
importance of	score $< \mu - \sigma$							-4.7393***	(1.2359)	-4.4559***	(1.0385)	-4.2882**	(1.7074)						
prox. (family)	score $> \mu + \sigma$							2.3129	(1.7638)	7.6354***	(1.6934)	10.7516***	(3.1493)						
importance of	score $< \mu - \sigma$							-2.1422	(1.3355)	-2.6721**	(1.2062)	-4.4311**	(1.7772)						
prox. (friends)	score $> \mu + \sigma$							5.9095***	(1.5368)	8.3919***	(1.6984)	13.5883***	(3.2296)						
previous mobility experiences (χ)																			
	residential move (yes=1)													-1.3372	(0.9365)	-0.0380	(1.0049)	1.5196	(1.4732)
	exchange participation (yes=1)													-1.4010	(0.8968)	-1.7218*	(0.9371)	-4.0944***	(1.3814)
	stay abroad (yes=1)													-7.1600***	(1.0396)	-6.7161***	(0.9863)	-7.5422***	(1.5591)
	educational mobility (km)													-0.0272***	(0.0033)	-0.0325***	(0.0042)	-0.0445***	(0.0055)
local conditions at origin (a_O)																			
	GDP (per capita)	-0.5814***	(0.1391)	-0.5919***	(0.1454)	-0.7449***	(0.2213)	-0.6236***	(0.1453)	-0.4419***	(0.1480)	-0.4836**	(0.2011)	-0.3695***	(0.1225)	-0.3755***	(0.1361)	-0.6700***	(0.2049)
	building land prices	0.0642***	(0.0241)	0.0732***	(0.0227)	0.0861***	(0.0318)	0.0799***	(0.0254)	0.0518**	(0.0230)	0.0509*	(0.0280)	0.0346	(0.0237)	0.0410**	(0.0207)	0.0729**	(0.0304)
	accessibility (train)	-0.0413	(0.0390)	-0.1156***	(0.0404)	-0.1491***	(0.0573)	-0.0475	(0.0372)	-0.0771*	(0.0409)	-0.0863	(0.0537)	-0.0333	(0.0351)	-0.0891**	(0.0377)	-0.1723***	(0.0527)
	accessibility (car)	0.0118	(0.0685)	0.0318	(0.0749)	0.0281	(0.1031)	0.0219	(0.0768)	-0.0148	(0.0769)	-0.0334	(0.0962)	0.0138	(0.0677)	0.0195	(0.0707)	0.1364	(0.1019)
	pop. density	-0.0012	(0.0014)	-0.0024	(0.0015)	-0.0029	(0.0020)	-0.0009	(0.0015)	-0.0003	(0.0014)	-0.0017	(0.0021)	0.0008	(0.0013)	-0.0007	(0.0014)	-0.0009	(0.0021)
	recreational area (per capita)	-0.0081	(0.0200)	0.0023	(0.0187)	-0.0053	(0.0232)	0.0089	(0.0207)	0.0123	(0.0162)	-0.0070	(0.0227)	0.0115	(0.0182)	0.0129	(0.0175)	0.0156	(0.0247)
	public services	-0.0127	(0.0303)	-0.0200	(0.0331)	-0.0061	(0.0474)	-0.0164	(0.0327)	-0.0266	(0.0298)	-0.0087	(0.0428)	0.0047	(0.0286)	0.0051	(0.0312)	0.0170	(0.0465)
	unemployment rate (π_{UO})	-0.6918*	(0.4071)	-0.7303*	(0.4400)	-0.9802	(0.5993)	-0.7467*	(0.4373)	-0.8447**	(0.4303)	-0.7334	(0.5674)	-0.8544**	(0.3647)	-0.8286**	(0.3926)	-1.0462*	(0.5957)
premium type controls		✓		✓		✓		✓		✓		✓		✓		✓		✓	
relative income control (w_0)		✓		✓		✓		✓		✓		✓		✓		✓		✓	
constant		✓		✓		✓		✓		✓		✓		✓		✓		✓	
observations		7404		7404		7404		7404		7404		7404		7404		7404		7404	
df (model)		31		31		31		37		37		37		35		35		35	
raw sum of deviation (rsd)		95347.54		141949.34		142658.09		95347.54		141949.34		142658.09		95347.54		141949.34		142658.09	
min. sum of deviations (msd)		82394.36		118970.42		114353.01		81544.18		117062.78		111921.97		81338.14		117707.56		113010.95	
pseudo R-squared (1-msd/rsd)		0.1359		0.1619		0.1984		0.1448		0.1753		0.2155		0.1469		0.1708		0.2078	

*** p<0.01, ** p<0.05, * p<0.1

Note: Standard errors are bootstrapped (500 replications) in Stata 14.2. The seed was each time set to 27644873, to ensure that across specifications the same 'random-sample' was drawn.

Table A6.5: OLS model comparison for internal mobility premiums

dependent variable		Δ_{A1} (internal, given alternative job)								Δ_{U1} (internal, given unemployment)							
estimation method		OLS								OLS							
		coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.
gender (female=1)		-0.2754	(1.3607)	-0.3371	(1.3480)	-1.4960	(1.3556)	0.4297	(1.3473)	2.6216*	(1.4682)	2.8011*	(1.4666)	2.3257	(1.4843)	3.3477**	(1.4602)
age		0.0180	(0.3101)	-0.0639	(0.3084)	-0.1137	(0.2996)	0.0180	(0.2999)	0.7400**	(0.3462)	0.7142**	(0.3526)	0.7237**	(0.3521)	0.8008**	(0.3476)
partnership (yes=1)		2.6884**	(1.2194)	2.6450**	(1.1963)	2.0262*	(1.1740)	2.3188*	(1.1877)	2.1686*	(1.3051)	2.2879*	(1.3092)	2.0672	(1.3077)	1.9241	(1.3077)
language skills (English)																	
	high	-1.8443	(1.9460)	-2.7612	(1.9491)	-1.8399	(1.9471)	-0.3757	(1.9498)	-1.1450	(2.2021)	-1.6557	(2.2455)	-1.2022	(2.2488)	0.2224	(2.2741)
	medium	-1.2629	(1.8354)	-1.7633	(1.8224)	-1.8264	(1.8135)	-0.8404	(1.7851)	-1.1890	(2.0863)	-1.5575	(2.0908)	-1.7100	(2.0845)	-0.8528	(2.0663)
risk attitude	score $< \mu - \sigma$	3.1846**	(1.5077)	2.9233*	(1.4966)	1.6322	(1.4718)	2.2153	(1.4697)	0.5549	(1.6063)	0.3686	(1.6067)	-0.2839	(1.6008)	-0.2770	(1.5939)
(career domain)	score $> \mu + \sigma$	0.5477	(1.8963)	0.8904	(1.8624)	1.2376	(1.8070)	1.4214	(1.8463)	-0.8674	(2.1095)	-0.8040	(2.1031)	-0.6316	(2.0846)	-0.3135	(2.0801)
patience	score $< \mu - \sigma$	3.3475*	(1.7617)	3.4679**	(1.7304)	3.6662**	(1.6992)	3.5408**	(1.7002)	2.6977	(1.9002)	2.7310	(1.8939)	2.9472	(1.8943)	2.8121	(1.8764)
	score $> \mu + \sigma$	-1.7687	(1.6247)	-1.1718	(1.6201)	-0.8614	(1.6146)	-0.7574	(1.6061)	-3.6211**	(1.8031)	-3.2577*	(1.8271)	-2.8791	(1.8276)	-2.8303	(1.8292)
extraversion	score $< \mu - \sigma$	5.1720***	(1.9347)	4.6889**	(1.9094)	2.8566	(1.8643)	4.1527**	(1.9249)	-0.8196	(2.2150)	-1.0448	(2.2027)	-2.4119	(2.2280)	-1.5828	(2.1927)
	score $> \mu + \sigma$	-0.4281	(1.5228)	-0.3319	(1.5174)	-0.2251	(1.5162)	0.0353	(1.4880)	0.8809	(1.7512)	1.0055	(1.7624)	1.1301	(1.7965)	1.3005	(1.7550)
neuroticism	score $< \mu - \sigma$	-1.7319	(1.8658)	-1.6723	(1.8652)	-1.1900	(1.8439)	-1.6520	(1.8429)	-1.5270	(1.9299)	-1.2849	(1.9480)	-0.6843	(2.0022)	-1.3034	(1.9478)
	score $> \mu + \sigma$	0.9757	(1.7301)	1.0067	(1.7238)	0.6262	(1.6956)	1.1728	(1.7160)	1.7053	(1.8513)	1.5464	(1.8839)	1.1666	(1.8819)	1.7221	(1.8638)
openness	score $< \mu - \sigma$	-1.9855	(1.5385)	-2.4274	(1.5033)	-3.2999**	(1.4750)	-2.6447*	(1.5000)	-0.4961	(1.7226)	-0.7922	(1.7057)	-1.2310	(1.7174)	-0.9933	(1.7137)
	score $> \mu + \sigma$	-3.0311*	(1.5762)	-2.4079	(1.5556)	-2.3652	(1.5261)	-2.5160*	(1.5282)	0.2133	(1.7293)	0.3043	(1.7293)	0.5349	(1.7184)	0.2689	(1.7120)
conscientious-	score $< \mu - \sigma$	-0.7820	(1.9077)	-0.1525	(1.8819)	-0.5956	(1.8328)	0.2161	(1.8488)	0.1943	(2.2764)	0.5812	(2.2605)	0.1756	(2.2332)	1.0219	(2.2566)
ness	score $> \mu + \sigma$	0.9818	(1.6742)	0.3506	(1.6577)	0.2078	(1.6080)	-0.1122	(1.6473)	-0.7409	(1.8008)	-1.0914	(1.8200)	-1.1224	(1.8036)	-1.4904	(1.8198)
agreeableness	score $< \mu - \sigma$	-0.4718	(1.5941)	-0.4783	(1.5660)	0.3669	(1.5429)	-0.9523	(1.5422)	0.5338	(1.7981)	0.4990	(1.8033)	0.8901	(1.7813)	0.1246	(1.7920)
	score $> \mu + \sigma$	2.9372*	(1.7180)	2.8646*	(1.7177)	2.8436*	(1.6753)	3.3087**	(1.6865)	2.6349	(1.7038)	2.5556	(1.7000)	2.6231	(1.6955)	2.9973*	(1.6809)
adaptability	score $< \mu - \sigma$					3.7570**	(1.6135)							3.6044**	(1.8360)		
	score $> \mu + \sigma$					-0.5820	(1.7576)							-0.8172	(1.8323)		
importance of	score $< \mu - \sigma$					-2.4222	(1.5239)							-1.0978	(1.7477)		
prox. (family)	score $> \mu + \sigma$					6.8367***	(2.1549)							-0.0820	(2.4020)		
importance of	score $< \mu - \sigma$					-4.4339***	(1.6334)							-2.9610	(1.8392)		
prox. (friends)	score $> \mu + \sigma$					6.6269***	(2.1258)							6.6505***	(2.5070)		
previous mobility experiences (χ)																	
	residential move (yes=1)							-0.0519	(1.3430)							-0.3737	(1.5510)
	exchange participation (yes=1)							-2.9656**	(1.2888)							-1.6391	(1.4162)
	stay abroad (yes=1)							-5.1171***	(1.5280)							-4.4696***	(1.5933)
	educational mobility (km)							-0.0286***	(0.0058)							-0.0280***	(0.0059)
local conditions at origin (a_O)																	
	GDP (per capita)			-0.5040**	(0.2032)	-0.4801**	(0.1962)	-0.4591**	(0.1968)			-0.4645**	(0.2101)	-0.4492**	(0.2093)	-0.4210**	(0.2022)
	building land prices			0.1024***	(0.0293)	0.0945***	(0.0285)	0.0923***	(0.0283)			0.0360	(0.0322)	0.0336	(0.0323)	0.0249	(0.0312)
	accessibility (train)			-0.0940*	(0.0532)	-0.0879*	(0.0517)	-0.0968*	(0.0520)			-0.0825	(0.0570)	-0.0828	(0.0580)	-0.0845	(0.0560)
	accessibility (car)			-0.0406	(0.0944)	-0.0680	(0.0920)	-0.0113	(0.0922)			0.0394	(0.1073)	0.0315	(0.1079)	0.0642	(0.1046)
	pop. density			-0.0035*	(0.0019)	-0.0038**	(0.0018)	-0.0028	(0.0019)			-0.0025	(0.0021)	-0.0028	(0.0021)	-0.0018	(0.0021)
	recreational area (per capita)			0.0148	(0.0237)	0.0137	(0.0224)	0.0248	(0.0230)			-0.0241	(0.0270)	-0.0254	(0.0276)	-0.0151	(0.0269)
	public services			-0.0536	(0.0426)	-0.0406	(0.0414)	-0.0277	(0.0419)			0.0359	(0.0478)	0.0410	(0.0477)	0.0611	(0.0473)
	unemployment rate (π_{UO})			-0.5356	(0.5585)	-0.4490	(0.5367)	-0.5613	(0.5466)			-0.5058	(0.6422)	-0.4025	(0.6359)	-0.5209	(0.6352)
relative income control (w_0)		✓		✓		✓		✓		✓		✓		✓		✓	
constant		✓		✓		✓		✓		✓		✓		✓		✓	
observations		1851		1851		1851		1851		1851		1851		1851		1851	
df (model)		20		28		34		32		20		28		34		32	
F-statistic		3.74		4.90		7.06		6.46		3.58		2.91		3.40		3.49	
prob > F		0.0000		0.0000		0.0000		0.0000		0.0000		0.0000		0.0000		0.0000	
R-squared		0.0340		0.0643		0.1084		0.0913		0.0473		0.0552		0.0691		0.0733	
adjusted R-squared		0.0234		0.0499		0.0917		0.0753		0.0369		0.0407		0.0517		0.0570	

*** p<0.01, ** p<0.05, * p<0.1

Note: Robust standard errors implemented.

Table A6.6: OLS model comparison for cross-border mobility premiums

dependent variable		Δ_{A2} (cross-border, given alternative job)								Δ_{U2} (cross-border, given unemployment)							
estimation method		OLS								OLS							
		coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.
gender (female=1)		-6.0137	(3.7504)	-6.1503*	(3.7349)	-9.2686**	(3.7252)	-3.5276	(3.7149)	-0.8478	(3.4449)	-0.9605	(3.3959)	-3.3063	(3.4290)	1.2224	(3.3833)
age		-0.8544	(0.8866)	-1.0549	(0.8528)	-1.1934	(0.8353)	-0.7391	(0.8230)	0.1484	(0.8586)	-0.0450	(0.8231)	-0.1133	(0.8072)	0.3177	(0.8027)
partnership (yes=1)		9.3967***	(3.4846)	8.8990**	(3.4689)	7.0816**	(3.3604)	8.1222**	(3.4298)	10.4596***	(3.0985)	9.8614***	(3.1135)	8.5555***	(3.0609)	8.9913***	(3.0766)
language skills (English)																	
	high	-23.6879***	(6.0125)	-23.9855***	(6.0491)	-21.0169***	(6.0630)	-16.1405***	(6.0409)	-17.1100***	(5.3224)	-16.4404***	(5.3669)	-14.1794***	(5.3794)	-9.4697*	(5.4445)
	medium	-10.2719*	(5.9435)	-10.6444*	(5.9288)	-10.7991*	(5.9179)	-7.5529	(5.8053)	-7.9837	(5.2263)	-7.7829	(5.1926)	-8.0775	(5.1861)	-4.9963	(5.1336)
risk attitude	score $< \mu - \sigma$	13.2469***	(4.2107)	13.1224***	(4.1659)	9.7278**	(4.0739)	10.9922***	(4.0828)	8.5952**	(3.8063)	8.8238**	(3.7748)	6.1141*	(3.6904)	6.9100*	(3.7431)
(career domain)	score $> \mu + \sigma$	3.6678	(6.2959)	4.2463	(6.1936)	5.5719	(6.0119)	5.7538	(6.1869)	-1.7722	(4.8820)	-1.5332	(4.8207)	-0.6342	(4.7400)	-0.2379	(4.7356)
patience	score $< \mu - \sigma$	7.5505	(5.0853)	7.4406	(5.0886)	8.3598	(5.0845)	7.6499	(5.0259)	7.2865	(4.8264)	6.8670	(4.7984)	7.6242	(4.7760)	7.0780	(4.7546)
	score $> \mu + \sigma$	-6.8922	(4.4869)	-5.4298	(4.4844)	-3.4816	(4.6783)	-4.1676	(4.3823)	-7.7745*	(3.9794)	-6.6895*	(3.9946)	-5.0524	(4.0449)	-5.4361	(3.9453)
extraversion	score $< \mu - \sigma$	12.1283*	(6.2902)	10.7611*	(6.2793)	5.4891	(6.1426)	9.0318	(6.3078)	0.6293	(5.2387)	-0.6305	(5.2056)	-5.6125	(5.1363)	-2.5483	(5.2071)
	score $> \mu + \sigma$	0.2911	(4.6062)	0.0617	(4.5765)	1.4610	(4.4801)	1.3488	(4.5047)	2.9835	(3.9327)	2.6501	(3.9034)	3.8816	(3.8931)	3.8275	(3.8340)
neuroticism	score $< \mu - \sigma$	0.8428	(6.4434)	0.7872	(6.5199)	3.0667	(6.3956)	1.1426	(6.4745)	-3.5265	(4.7860)	-3.2135	(4.8331)	-1.0162	(4.8609)	-2.7380	(4.8427)
	score $> \mu + \sigma$	-4.1235	(4.4400)	-3.8519	(4.4106)	-5.0932	(4.3041)	-3.2470	(4.3748)	-0.2463	(4.2487)	0.2761	(4.2595)	-1.1421	(4.1924)	0.9865	(4.1851)
openness	score $< \mu - \sigma$	-1.8502	(4.5841)	-2.0937	(4.4778)	-4.5068	(4.3346)	-2.5682	(4.4565)	2.1728	(4.3009)	2.3202	(4.2285)	0.3821	(4.1415)	2.0481	(4.2091)
	score $> \mu + \sigma$	-1.2311	(4.6136)	-0.4385	(4.6578)	-0.2233	(4.5450)	-0.7081	(4.6013)	0.6780	(4.1971)	0.8536	(4.1840)	1.2504	(4.0754)	0.7576	(4.1274)
conscientious-	score $< \mu - \sigma$	-2.3040	(5.8102)	-1.7193	(5.8420)	-2.9595	(5.6966)	-0.7835	(5.7597)	1.6912	(5.3993)	1.6789	(5.3961)	0.4247	(5.2267)	2.6113	(5.3658)
ness	score $> \mu + \sigma$	-0.6871	(4.4168)	-1.4370	(4.4034)	-1.5782	(4.3199)	-2.7937	(4.3688)	-2.0627	(3.9494)	-1.9653	(3.9242)	-2.1311	(3.8764)	-3.2059	(3.9287)
agreeableness	score $< \mu - \sigma$	-0.5264	(4.4674)	-0.8929	(4.4424)	1.3764	(4.3966)	-2.2011	(4.4062)	1.4352	(4.0697)	0.8931	(4.0754)	2.4783	(4.0184)	-0.1865	(4.0249)
	score $> \mu + \sigma$	0.8986	(4.5888)	0.6592	(4.6368)	0.6889	(4.4942)	1.7845	(4.5093)	-1.6250	(4.0266)	-1.9670	(4.0488)	-1.8457	(3.9522)	-0.9563	(3.9567)
adaptability	score $< \mu - \sigma$					10.3582**	(4.5175)							11.5933***	(4.2287)		
	score $> \mu + \sigma$					-8.0209	(5.4676)							-6.8498*	(4.0174)		
importance of	score $< \mu - \sigma$					-6.3241	(4.6587)							-4.2507	(3.8046)		
prox. (family)	score $> \mu + \sigma$					19.4954***	(5.6287)							11.9865**	(5.4871)		
importance of	score $< \mu - \sigma$					-12.3053**	(4.9182)							-9.2513**	(4.0285)		
prox. (friends)	score $> \mu + \sigma$					16.4754***	(6.1202)							16.4393***	(5.9998)		
previous mobility experiences (χ)																	
	residential move (yes=1)							-1.0536	(4.0234)							-0.1666	(3.5511)
	exchange participation (yes=1)							-8.8576**	(3.5232)							-4.6446	(3.2129)
	stay abroad (yes=1)							-18.5417***	(3.8474)							-18.6614***	(3.3043)
	educational mobility (km)							-0.0682***	(0.0164)							-0.0571***	(0.0140)
local conditions at origin (a_O)																	
	GDP (per capita)			-1.5941***	(0.5946)	-1.5469***	(0.5845)	-1.4747**	(0.5766)			-1.4120***	(0.5365)	-1.3704***	(0.5314)	-1.3098**	(0.5166)
	building land prices			0.2146**	(0.0858)	0.1938**	(0.0844)	0.1893**	(0.0837)			0.1125	(0.0813)	0.0975	(0.0804)	0.0887	(0.0785)
	accessibility (train)			-0.2887**	(0.1444)	-0.2809**	(0.1426)	-0.2994**	(0.1418)			-0.3253**	(0.1350)	-0.3244**	(0.1341)	-0.3339**	(0.1315)
	accessibility (car)			0.1309	(0.2845)	0.0663	(0.2818)	0.2000	(0.2798)			0.1028	(0.2656)	0.0600	(0.2635)	0.1498	(0.2602)
	pop. density			-0.0029	(0.0064)	-0.0033	(0.0063)	-0.0011	(0.0063)			-0.0006	(0.0059)	-0.0011	(0.0059)	0.0009	(0.0058)
	recreational area (per capita)			0.1038	(0.0728)	0.1057	(0.0717)	0.1306*	(0.0716)			0.0907	(0.0726)	0.0917	(0.0722)	0.1149	(0.0715)
	public services			-0.1222	(0.1319)	-0.0868	(0.1284)	-0.0523	(0.1313)			-0.0116	(0.1163)	0.0147	(0.1151)	0.0506	(0.1148)
	unemployment rate (π_{UO})			-2.9696	(1.8238)	-2.8003	(1.7997)	-3.1068*	(1.7974)			-3.0419*	(1.7414)	-2.8448*	(1.7278)	-3.2171*	(1.7162)
relative income control (w_0)		✓		✓		✓		✓		✓		✓		✓		✓	
constant		✓		✓		✓		✓		✓		✓		✓		✓	
observations		1851		1851		1851		1851		1851		1851		1851		1851	
df (model)		20		28		34		32		20		28		34		32	
F-statistic		4.48		3.83		5.67		6.14		4.61		3.79		5.06		5.62	
prob > F		0.0000		0.0000		0.0000		0.0000		0.0000		0.0000		0.0000		0.0000	
R-squared		0.0372		0.0505		0.0906		0.0770		0.0442		0.0551		0.0895		0.0808	
adjusted R-squared		0.0267		0.0359		0.0736		0.0607		0.0338		0.0405		0.0724		0.0646	

*** p<0.01, ** p<0.05, * p<0.1

Note: Robust standard errors implemented.

Table A6.7: Scenario-specific outcomes for the lower and upper quartile

dependent variable		Δ_{A1} (internal, given alternative job)				Δ_{U1} (internal, given unemployment)				Δ_{A2} (cross-border, given alternative job)				Δ_{U2} (cross-border, given unemployment)			
estimation method		QREG ($q = 0.25$)		QREG ($q = 0.75$)		QREG ($q = 0.25$)		QREG ($q = 0.75$)		QREG ($q = 0.25$)		QREG ($q = 0.75$)		QREG ($q = 0.25$)		QREG ($q = 0.75$)	
		coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.
gender (female=1)		-0.5514	(1.3049)	-1.1452	(1.9107)	-0.1485	(1.8212)	2.3268	(2.0003)	-6.0010**	(2.4162)	-10.2627*	(5.5936)	0.2561	(2.8390)	-4.5290	(4.5012)
age		0.0510	(0.2291)	-0.1172	(0.4587)	0.5872	(0.3822)	0.5156	(0.4770)	0.4742	(0.5368)	-1.3325	(0.9990)	0.7312	(0.5801)	-0.4730	(0.8551)
partnership (yes=1)		2.6877**	(1.0866)	-0.1705	(1.7388)	1.4531	(1.5714)	0.6411	(1.8855)	5.0617**	(2.1013)	7.0716	(4.9984)	4.7411**	(2.3712)	11.1132**	(4.3624)
language skills (English)																	
	high	-0.4046	(1.8103)	0.1947	(2.8222)	4.6485	(3.0917)	3.1436	(3.0299)	-9.4784**	(4.1531)	-22.4253**	(9.3049)	-7.8203*	(4.0401)	-4.9535	(7.3526)
	medium	-0.8469	(1.6510)	-0.7880	(2.7043)	3.6963	(2.8210)	-0.5641	(2.7155)	-3.9708	(3.3971)	-17.0999*	(9.0547)	-4.2663	(3.8003)	-1.8373	(7.2207)
risk attitude	score $< \mu - \sigma$	0.1372	(1.1975)	1.7404	(2.1718)	-1.2295	(1.8068)	-0.6930	(2.2159)	1.5936	(2.7369)	12.0002**	(5.8736)	1.4971	(2.8312)	6.4503	(4.9617)
(career domain)	score $> \mu + \sigma$	-1.2148	(1.6475)	3.2953	(2.4320)	1.0199	(2.4597)	0.1987	(2.7438)	-3.0593	(3.8952)	2.4121	(9.0048)	-1.2711	(3.3699)	4.4859	(6.7649)
patience	score $< \mu - \sigma$	0.7383	(1.3673)	3.8367	(2.4133)	1.9709	(2.2896)	3.4410	(2.7562)	**-0.6687**	(3.4630)	**15.5012****	(7.1867)	2.3893	(3.4850)	6.7044	(6.5318)
	score $> \mu + \sigma$	-0.0716	(1.4483)	-0.3768	(2.3061)	-4.0820	(2.7113)	-1.3159	(2.2433)	-0.4686	(3.5461)	1.4412	(6.2554)	-4.2295	(3.6775)	-3.7317	(5.6925)
extraversion	score $< \mu - \sigma$	1.6350	(1.4770)	1.7856	(2.8444)	-5.8248**	(2.7895)	-2.2271	(3.7770)	2.7268	(3.4029)	-6.2711	(7.6233)	-6.4132*	(3.6111)	-4.3021	(6.2815)
	score $> \mu + \sigma$	-0.3637	(1.2582)	1.3161	(2.3149)	**-3.7943***	(2.0512)	**2.7059**	(2.3936)	-1.4353	(3.0414)	7.4033	(6.9343)	-1.4136	(3.0732)	6.8599	(5.4733)
neuroticism	score $< \mu - \sigma$	-1.6990	(1.4657)	-4.1182	(2.6621)	0.1042	(2.4876)	-3.6994	(3.0000)	-6.8427**	(3.3577)	0.7498	(8.6338)	-2.6948	(3.9822)	-5.9342	(5.7734)
	score $> \mu + \sigma$	0.6556	(1.5068)	1.9467	(2.4581)	1.9399	(2.0029)	2.3323	(2.9636)	-0.1499	(3.6263)	-4.0800	(6.2132)	-0.2514	(3.1628)	-0.6008	(5.4244)
openness	score $< \mu - \sigma$	-2.2380*	(1.2998)	-1.2694	(2.1939)	-1.4467	(2.1192)	0.2640	(2.5832)	-2.0061	(2.7203)	-5.3696	(5.7361)	-4.0573	(2.7816)	-0.7699	(5.0711)
	score $> \mu + \sigma$	-1.9856	(1.4127)	-2.0203	(2.4474)	1.2967	(1.9464)	-0.7064	(2.3018)	-4.8425	(2.9945)	3.0424	(6.3547)	-0.2313	(3.0014)	-0.7605	(5.3054)
conscientious-	score $< \mu - \sigma$	-1.0550	(1.8419)	-1.1820	(3.0571)	-1.4907	(2.9591)	1.3682	(3.0957)	-3.2999	(3.9937)	-1.5050	(8.3182)	-4.2795	(4.2253)	0.3729	(6.8597)
ness	score $> \mu + \sigma$	-1.0309	(1.3256)	3.5574	(2.4526)	-2.4780	(2.5394)	-1.3515	(2.8616)	-0.2562	(3.1207)	5.7850	(6.5407)	-3.8531	(3.7405)	0.0590	(5.6927)
agreeableness	score $< \mu - \sigma$	-0.5571	(1.3136)	-0.8357	(2.1862)	-2.1626	(1.9960)	1.6875	(2.3232)	-1.5081	(2.7384)	0.9321	(6.2484)	0.5443	(3.1105)	1.6277	(5.5255)
	score $> \mu + \sigma$	2.2609	(1.3961)	4.4815*	(2.3390)	2.3730	(1.8355)	2.6927	(2.4149)	3.8596	(2.9918)	3.6458	(6.6325)	3.1260	(3.2690)	-0.5152	(4.5466)
adaptability	score $< \mu - \sigma$	**0.0761**	(1.4951)	**7.0026*****	(2.5681)	3.7466*	(1.9775)	2.8919	(2.9225)	1.6706	(3.3802)	10.1880	(8.1504)	5.7540*	(3.1808)	9.4159	(6.1988)
	score $> \mu + \sigma$	-0.3694	(1.4106)	0.0536	(2.5262)	4.0195*	(2.3843)	-1.2342	(2.4685)	-5.3278	(4.0082)	-12.4717*	(7.2963)	3.5153	(3.6323)	-3.1857	(5.3266)
importance of	score $< \mu - \sigma$	-3.5212**	(1.4530)	-1.6608	(2.1478)	-0.7178	(2.1008)	-3.4211	(2.8664)	-6.6036**	(2.8546)	-10.0707*	(6.0260)	-2.8205	(3.0965)	-5.7766	(4.8657)
prox. (family)	score $> \mu + \sigma$	3.0480	(2.0804)	5.4371*	(3.1250)	-0.9602	(2.7848)	0.8737	(3.9460)	16.8306***	(4.9553)	24.7437***	(8.7659)	7.8599*	(4.6302)	18.3010**	(7.3340)
importance of	score $< \mu - \sigma$	-2.3042*	(1.3912)	-5.7381***	(2.2166)	2.5288	(2.5960)	-1.9884	(2.9209)	**-0.9695**	(3.4277)	**-15.8228****	(6.5589)	-2.9635	(3.2838)	-8.2848*	(4.7987)
prox. (friends)	score $> \mu + \sigma$	5.2347***	(1.8305)	9.6560***	(3.5938)	3.4466	(2.8381)	6.3881	(4.2648)	7.6810	(4.7712)	22.6245**	(9.3671)	5.8574	(4.9448)	18.1490*	(9.7014)
previous mobility experiences (χ)																	
	residential move (yes=1)	-0.5517	(1.2240)	0.0872	(2.0215)	-0.6412	(1.8479)	0.9444	(2.5590)	-1.2577	(3.0659)	-1.1266	(5.6291)	-1.0730	(2.6432)	4.5686	(4.7829)
	exchange participation (yes=1)	-0.9756	(1.1243)	-2.5767	(1.8652)	-1.2589	(1.7190)	-0.0064	(2.0584)	**-1.6242**	(2.6908)	**-12.2384****	(4.7533)	0.3702	(2.3408)	-5.5607	(4.5232)
	stay abroad (yes=1)	-3.9569***	(1.3121)	-3.8678*	(2.1062)	-2.0172	(1.9079)	-5.8404**	(2.2720)	-11.9094***	(3.1619)	-14.2863***	(4.9921)	-9.4402***	(2.9679)	-11.8485***	(4.5905)
	educational mobility (km)	-0.0239***	(0.0052)	-0.0228***	(0.0073)	**-0.0183****	(0.0071)	**-0.0364*****	(0.0087)	-0.0271**	(0.0112)	-0.0590***	(0.0199)	**-0.0265*****	(0.0097)	**-0.0595*****	(0.0166)
local conditions at origin (a_O)																	
	GDP (per capita)	-0.2136	(0.1726)	-0.4625*	(0.2386)	-0.4851*	(0.2538)	-0.0335	(0.2775)	-0.6129*	(0.3673)	-1.2720	(0.9193)	-0.9090**	(0.3983)	-1.1753	(0.7319)
	building land prices	0.0359	(0.0276)	0.0813**	(0.0349)	0.0455	(0.0439)	-0.0168	(0.0436)	0.0979	(0.0630)	0.1788	(0.1297)	0.0640	(0.0716)	0.0022	(0.0984)
	accessibility (train)	**0.0356**	(0.0441)	**-0.1249****	(0.0634)	-0.0455	(0.0605)	-0.0327	(0.0782)	-0.0194	(0.1040)	-0.3364	(0.2340)	-0.0997	(0.1211)	-0.2720	(0.2016)
	accessibility (car)	-0.1322	(0.0820)	-0.0446	(0.1255)	0.0479	(0.1302)	0.0218	(0.1523)	0.0648	(0.1802)	0.3948	(0.4271)	0.0186	(0.2284)	0.0397	(0.3361)
	pop. density	-0.0010	(0.0017)	-0.0028	(0.0027)	-0.0028	(0.0030)	0.0004	(0.0031)	0.0009	(0.0036)	0.0037	(0.0082)	-0.0002	(0.0038)	-0.0001	(0.0067)
	recreational area (per capita)	-0.0079	(0.0243)	0.0162	(0.0298)	-0.0051	(0.0345)	-0.0249	(0.0356)	0.0099	(0.0502)	0.1203	(0.1006)	0.0275	(0.0559)	0.0279	(0.0908)
	public services	-0.0160	(0.0356)	-0.0027	(0.0554)	0.0385	(0.0592)	0.0296	(0.0645)	-0.0339	(0.0813)	-0.0984	(0.1930)	0.0573	(0.0909)	0.1808	(0.1478)
	unemployment rate (π_{UO})	-0.4563	(0.4722)	-0.4633	(0.7900)	-0.4669	(0.8630)	-0.2442	(0.8077)	-0.7892	(1.1922)	-3.0587	(2.2182)	-1.1794	(1.1669)	-2.5244	(2.0071)
relative income control (w_0)		✓		✓		✓		✓		✓		✓		✓		✓	
constant		✓		✓		✓		✓		✓		✓		✓		✓	
observations		1851		1851		1851		1851		1851		1851		1851		1851	
df (model)		38		38		38		38		38		38		38		38	
raw sum of deviation (rsd)		11914.14		15786.85		15076.40		16611.08		29869.33		44162.07		27946.30		39771.67	
minimum sum of deviations (msd)		10734.52		14312.74		14136.39		15825.43		27678.50		41191.68		26396.51		36634.92	
pseudo R-squared (1-msd/rsd)		0.0990		0.0934		0.0623		0.0473		0.0733		0.0673		0.0555		0.0789	

*** p<0.01, ** p<0.05, * p<0.1

Note: The corresponding results for the median ($q = 0.50$) are reported in Table 6.2 and Table 6.3. Standard errors in the simultaneous quantile regressions are bootstrapped (500 replications). The standard errors are also used in the test for coefficient equality across the three quantiles. Depicted coefficients in bold indicate significant differences of quantile coefficients at the conventional significance levels.

Table A6.8: Model comparison for sensitivity check (A) – the theory of planned behaviour

dependent variable		Δ_{A1} (internal, given alternative job)				Δ_{U1} (internal, given unemployment)				Δ_{A2} (Europe, given alternative job)				Δ_{U2} (Europe, given unemployment)			
estimation method		OLS				OLS				OLS				OLS			
		coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.
gender (female=1)		0.7977	(1.2948)	-0.1912	(1.3138)	3.7324**	(1.4573)	3.3255**	(1.4795)	-2.5250	(3.5927)	-5.0556	(3.6396)	2.0589	(3.3072)	0.2012	(3.3869)
age		-0.0714	(0.2992)	-0.1286	(0.2931)	0.6905**	(0.3520)	0.6922*	(0.3533)	-1.5002*	(0.8196)	-1.5782*	(0.8129)	-0.4201	(0.8013)	-0.4358	(0.7960)
partnership (yes=1)		1.6361	(1.1538)	1.2952	(1.1431)	1.7543	(1.2965)	1.6894	(1.2984)	5.1065	(3.3393)	4.3552	(3.2792)	6.9534**	(3.0418)	6.4961**	(3.0180)
language skills (English)																	
	high	-1.5686	(1.9113)	-1.1848	(1.9209)	-0.8625	(2.2149)	-0.6768	(2.2227)	-14.1605**	(6.0578)	-13.7595**	(6.0549)	-8.4952	(5.3752)	-8.2329	(5.3823)
	medium	-1.0327	(1.7848)	-1.2692	(1.7893)	-0.9927	(2.0585)	-1.2558	(2.0564)	-6.0516	(5.8990)	-7.0968	(5.9142)	-3.7444	(5.1725)	-4.7714	(5.1871)
risk attitude	score $< \mu - \sigma$	1.5074	(1.4348)	0.5892	(1.4264)	-0.6088	(1.5824)	-1.0295	(1.5833)	8.3697**	(4.0413)	6.4495	(4.0078)	4.8268	(3.7045)	3.3835	(3.6707)
(career domain)	score $> \mu + \sigma$	1.3181	(1.7885)	1.4147	(1.7494)	-0.6817	(2.0593)	-0.6549	(2.0423)	7.2555	(6.0639)	7.4599	(5.9260)	0.5421	(4.5855)	0.6083	(4.5532)
patience	score $< \mu - \sigma$	3.0081*	(1.6829)	3.0541*	(1.6597)	2.3332	(1.8827)	2.4719	(1.8805)	5.6998	(4.8433)	6.2877	(4.8498)	5.3701	(4.6350)	5.9402	(4.6162)
	score $> \mu + \sigma$	0.6364	(1.5641)	0.4910	(1.5625)	-2.1012	(1.8361)	-1.9865	(1.8308)	-1.4724	(4.1297)	-1.0170	(4.3673)	-4.1255	(3.8093)	-3.5169	(3.8946)
extraversion	score $< \mu - \sigma$	2.5964	(1.8818)	1.5724	(1.8297)	-2.1144	(2.1710)	-3.0999	(2.1924)	7.6966	(6.1991)	4.6011	(6.0566)	-2.9310	(5.2019)	-6.2129	(5.1018)
	score $> \mu + \sigma$	0.2868	(1.4772)	0.0075	(1.4818)	1.3289	(1.7524)	1.2632	(1.7831)	3.8087	(4.4443)	4.0346	(4.3395)	5.5840	(3.7745)	6.0611	(3.7790)
neuroticism	score $< \mu - \sigma$	-1.3399	(1.7580)	-1.3318	(1.7509)	-1.0297	(1.9324)	-0.6240	(1.9876)	1.8678	(6.1749)	2.8656	(6.0762)	-2.3387	(4.6000)	-0.9582	(4.6641)
	score $> \mu + \sigma$	0.8825	(1.6796)	0.7407	(1.6649)	1.4425	(1.8639)	1.1729	(1.8644)	-6.9089*	(4.1918)	-7.1904*	(4.1595)	-2.5181	(4.0743)	-3.1742	(4.0506)
openness	score $< \mu - \sigma$	-3.0217**	(1.4772)	-3.6122**	(1.4602)	-1.5336	(1.6882)	-1.8348	(1.6990)	-5.0900	(4.4034)	-6.3811	(4.3176)	-0.4402	(4.1438)	-1.4709	(4.1035)
	score $> \mu + \sigma$	-1.8216	(1.4940)	-1.8613	(1.4752)	0.6321	(1.7074)	0.8344	(1.6985)	1.4252	(4.4580)	1.2149	(4.4040)	2.0563	(4.0628)	2.1691	(3.9957)
conscientious-	score $< \mu - \sigma$	-0.0877	(1.7909)	-0.2720	(1.7682)	0.9448	(2.2372)	0.7148	(2.2167)	-2.4433	(5.5610)	-3.1328	(5.4743)	0.7274	(5.2727)	-0.0621	(5.1350)
ness	score $> \mu + \sigma$	-0.1825	(1.5742)	-0.2434	(1.5524)	-1.5098	(1.8029)	-1.4588	(1.7957)	-2.4506	(4.1616)	-2.5994	(4.1672)	-3.7114	(3.6985)	-3.8092	(3.7165)
agreeableness	score $< \mu - \sigma$	0.2853	(1.5069)	0.8626	(1.4977)	1.0726	(1.7685)	1.3004	(1.7492)	-0.2443	(4.2788)	1.2146	(4.2714)	1.4049	(3.9240)	2.3317	(3.8957)
	score $> \mu + \sigma$	2.1324	(1.6771)	2.1624	(1.6475)	2.0683	(1.6847)	2.1711	(1.6849)	1.6373	(4.4132)	1.5706	(4.3524)	-1.4907	(3.9157)	-1.4366	(3.8729)
adaptability	score $< \mu - \sigma$			2.7233*	(1.5967)			3.4222*	(1.8253)			7.9118*	(4.4388)			9.8387**	(4.1688)
	score $> \mu + \sigma$			1.0557	(1.7687)			-0.1262	(1.8686)			-3.6422	(5.5611)			-4.4254	(4.0326)
importance of	score $< \mu - \sigma$			-1.0756	(1.4995)			-0.6763	(1.7275)			-2.1610	(4.6599)			-1.3607	(3.7842)
prox. (family)	score $> \mu + \sigma$			6.0207***	(2.0897)			-0.6248	(2.3746)			14.9902***	(5.4109)			7.6889	(5.3338)
importance of	score $< \mu - \sigma$			-4.1379***	(1.5807)			-2.7325	(1.8322)			-9.3149**	(4.7199)			-7.0559*	(3.9848)
prox. (friends)	score $> \mu + \sigma$			4.7171**	(2.0737)			5.3770**	(2.4356)			10.5211*	(5.9034)			11.3254*	(5.8121)
riskiness of move (θ_R)																	
	score $< \mu - \sigma$	-4.8123***	(1.3533)	-4.2221***	(1.3978)	-2.2633	(1.4790)	-1.6787	(1.5190)	-18.8435***	(4.0904)	-15.9753***	(4.3975)	-11.7192***	(3.8324)	-8.9871**	(3.9842)
	score $> \mu + \sigma$	3.3500**	(1.6644)	1.4589	(1.7231)	-0.0223	(1.8963)	-1.2653	(1.9136)	10.9684*	(6.1078)	6.4857	(6.1614)	13.2192**	(6.0942)	9.6221	(6.3282)
likelihood of move (θ_M)																	
	score $< \mu - \sigma$	15.7505***	(1.7856)	14.2120***	(1.7744)	11.1021***	(1.9752)	10.2431***	(1.9640)	36.8221***	(5.8463)	33.5317***	(5.7405)	31.1888***	(5.4040)	28.6905***	(5.3329)
	score $> \mu + \sigma$	-3.1543**	(1.3694)	-3.4140**	(1.3614)	-2.5391	(1.5772)	-2.5474	(1.5779)	-24.6188***	(3.3263)	-21.7863***	(3.4413)	-17.3248***	(2.9345)	-14.8970***	(2.9964)
local conditions at origin (a_O)																	
	GDP (per capita)	-0.3527*	(0.1851)	-0.3518*	(0.1833)	-0.3746*	(0.1978)	-0.3754*	(0.1985)	-1.4211***	(0.5484)	-1.4166**	(0.5503)	-1.2605***	(0.4875)	-1.2579**	(0.4924)
	building land prices	0.0589**	(0.0269)	0.0557**	(0.0267)	0.0039	(0.0314)	0.0049	(0.0316)	0.1895**	(0.0801)	0.1770**	(0.0807)	0.0900	(0.0750)	0.0829	(0.0757)
	accessibility (train)	-0.0712	(0.0499)	-0.0687	(0.0498)	-0.0643	(0.0574)	-0.0679	(0.0584)	-0.2658*	(0.1390)	-0.2628*	(0.1390)	-0.2881**	(0.1299)	-0.2930**	(0.1305)
	accessibility (car)	-0.0518	(0.0906)	-0.0721	(0.0904)	0.0309	(0.1074)	0.0281	(0.1082)	0.0634	(0.2717)	0.0254	(0.2735)	0.0321	(0.2531)	0.0149	(0.2546)
	pop. density	-0.0015	(0.0019)	-0.0019	(0.0018)	-0.0011	(0.0021)	-0.0014	(0.0021)	-0.0012	(0.0061)	-0.0018	(0.0061)	0.0005	(0.0057)	-0.0000	(0.0057)
	recreational area (per capita)	0.0262	(0.0225)	0.0231	(0.0219)	-0.0193	(0.0273)	-0.0211	(0.0279)	0.1315*	(0.0686)	0.1277*	(0.0691)	0.1059	(0.0687)	0.1038	(0.0696)
	public services	-0.0116	(0.0401)	-0.0052	(0.0397)	0.0713	(0.0471)	0.0721	(0.0472)	-0.0727	(0.1243)	-0.0538	(0.1238)	0.0389	(0.1092)	0.0509	(0.1102)
	unemployment rate (π_{UO})	-0.6631	(0.5257)	-0.6107	(0.5154)	-0.6077	(0.6350)	-0.5251	(0.6332)	-3.1408*	(1.7336)	-3.0347*	(1.7339)	-3.0619*	(1.6713)	-2.9194*	(1.6776)
relative income control (w_0)		✓		✓		✓		✓		✓		✓		✓		✓	
constant		✓		✓		✓		✓		✓		✓		✓		✓	
observations		1842		1842		1842		1842		1842		1842		1842		1842	
df (model)		32		38		32		38		32		38		32		38	
F-statistic		8.41		8.91		3.79		3.69		8.84		8.71		6.85		6.83	
prob > F		0.0000		0.0000		0.0000		0.0000		0.0000		0.0000		0.0000		0.0000	
R-squared		0.1403		0.1647		0.0834		0.0920		0.1289		0.1462		0.1185		0.1340	
adjusted R-squared		0.1250		0.1471		0.0672		0.0729		0.1134		0.1282		0.1029		0.1158	

*** p<0.01, ** p<0.05, * p<0.1

Note: Statistical inference relies on robust standard errors. Measures of behavioural control (θ_R) and migration intention (θ_M) are accordingly conditioned, either with reference to an interstate or a cross-border move to another country in Europe.

Table A6.9: Model comparison for sensitivity check (B) – labour market readiness in internal migration scenarios

dependent variable		Δ_{A1} (internal, given alternative job)				Δ_{U1} (internal, given unemployment)			
estimation method		OLS				OLS			
		coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.
gender (female=1)		0.5474	(1.3245)	-0.4297	(1.3637)	3.6097**	(1.4897)	3.0167**	(1.4920)
age		0.3266	(0.3718)	0.2404	(0.3812)	0.9063**	(0.4616)	0.8971**	(0.4571)
partnership (yes=1)		1.1457	(1.1469)	1.7962	(1.1754)	1.5990	(1.3068)	2.0202	(1.3147)
language skills (English)									
	high	0.7215	(1.9335)	0.4861	(1.9627)	0.9571	(2.2832)	0.8357	(2.2883)
	medium	-0.5871	(1.7689)	-0.9334	(1.7933)	-0.6518	(2.0515)	-0.7649	(2.0532)
risk attitude	score $< \mu - \sigma$	0.1105	(1.4216)	0.8499	(1.4655)	-1.5581	(1.5808)	-1.0037	(1.5989)
(career domain)	score $> \mu + \sigma$	1.4816	(1.7543)	1.4945	(1.7997)	-0.4883	(2.0312)	-0.3017	(2.0630)
patience	score $< \mu - \sigma$	3.0844*	(1.6493)	3.7162**	(1.6807)	2.3871	(1.8648)	2.8702	(1.8753)
	score $> \mu + \sigma$	0.3163	(1.5603)	-0.7918	(1.6049)	-2.1492	(1.8342)	-2.7335	(1.8291)
extraversion	score $< \mu - \sigma$	1.4367	(1.8556)	2.6822	(1.8986)	-3.3099	(2.1876)	-2.5683	(2.2220)
	score $> \mu + \sigma$	-0.0474	(1.4768)	-0.1303	(1.5039)	1.3598	(1.7808)	1.4782	(1.7900)
neuroticism	score $< \mu - \sigma$	-1.4447	(1.7533)	-1.4221	(1.8383)	-0.8634	(1.9905)	-0.7481	(2.0017)
	score $> \mu + \sigma$	1.1927	(1.6699)	0.9277	(1.7068)	1.6829	(1.8544)	1.4493	(1.8688)
openness	score $< \mu - \sigma$	-3.3422**	(1.4602)	-3.3125**	(1.4838)	-1.7396	(1.7024)	-1.6912	(1.7123)
	score $> \mu + \sigma$	-2.1592	(1.4617)	-2.5747*	(1.5064)	0.5987	(1.6889)	0.2961	(1.7079)
conscientious-	score $< \mu - \sigma$	-0.2034	(1.7632)	-0.2921	(1.8105)	0.9653	(2.2109)	0.7021	(2.2267)
ness	score $> \mu + \sigma$	-0.4301	(1.5484)	-0.3386	(1.6135)	-1.7675	(1.8037)	-1.7980	(1.8156)
agreeableness	score $< \mu - \sigma$	0.4278	(1.4857)	-0.1545	(1.5287)	0.8378	(1.7451)	0.5385	(1.7733)
	score $> \mu + \sigma$	2.2762	(1.6339)	3.1485*	(1.6560)	2.3538	(1.6717)	2.9578*	(1.6805)
adaptability	score $< \mu - \sigma$	2.4963	(1.5943)	3.2797**	(1.6072)	3.1817*	(1.8331)	3.2712*	(1.8435)
	score $> \mu + \sigma$	1.9230	(1.8137)	0.9775	(1.8049)	0.9509	(1.9039)	0.7123	(1.8783)
importance of	score $< \mu - \sigma$	-0.8441	(1.5043)	-1.8472	(1.5298)	-0.1501	(1.7356)	-0.6119	(1.7346)
prox. (family)	score $> \mu + \sigma$	5.8309***	(2.0777)	6.6505***	(2.1268)	-0.6580	(2.3695)	-0.2661	(2.3892)
importance of	score $< \mu - \sigma$	-4.3905***	(1.5807)	-4.4783***	(1.6252)	-3.0694*	(1.8555)	-3.0718*	(1.8580)
prox. (friends)	score $> \mu + \sigma$	4.5366**	(2.0748)	5.9935***	(2.1080)	5.0301**	(2.4355)	5.8205**	(2.4901)
riskiness of move (θ_R)									
	score $< \mu - \sigma$	-3.7522***	(1.3847)			-1.1092	(1.5158)		
	score $> \mu + \sigma$	0.9590	(1.7481)			-1.7538	(1.9347)		
likelihood of move (θ_M)									
	score $< \mu - \sigma$	13.7071***	(1.7604)			9.4763***	(1.9426)		
	score $> \mu + \sigma$	-2.3489*	(1.3893)			-1.1585	(1.5719)		
work experience									
	part-time (or mini-job)	1.5840	(1.4169)	1.5188	(1.4554)	-0.0237	(1.6414)	-0.0706	(1.6576)
	full-time	-0.4023	(1.7919)	-0.5004	(1.8484)	-3.6981	(2.2784)	-3.6555	(2.3074)
vocational training (yes=1)		-1.7094	(1.9620)	-0.3838	(2.0513)	2.8745	(2.4055)	3.6946	(2.4573)
master student (yes=1)		-9.4267***	(2.7827)	-10.0417***	(2.8221)	-8.4636**	(3.5092)	-8.9157**	(3.5211)
previous mobility experiences (χ)									
	residential move (yes=1)	0.7426	(1.3165)	0.5787	(1.3316)	-0.0344	(1.5500)	-0.2618	(1.5588)
	exchange participation (yes=1)	-1.8492	(1.2524)	-2.6960**	(1.2743)	-0.8470	(1.4152)	-1.3566	(1.4250)
	stay abroad (yes=1)	-3.8809***	(1.4740)	-4.3580***	(1.5255)	-3.5719**	(1.6369)	-3.6639**	(1.6307)
	educational mobility (km)	-0.0128**	(0.0058)	-0.0227***	(0.0059)	-0.0179***	(0.0060)	-0.0234***	(0.0060)
local conditions at origin (a_O)									
	GDP (per capita)	-0.3539*	(0.1829)	-0.4501**	(0.1916)	-0.3670*	(0.1956)	-0.4164**	(0.2013)
	building land prices	0.0575**	(0.0265)	0.0861***	(0.0277)	0.0030	(0.0309)	0.0207	(0.0311)
	accessibility (train)	-0.0721	(0.0491)	-0.0841*	(0.0505)	-0.0728	(0.0580)	-0.0757	(0.0571)
	accessibility (car)	-0.0598	(0.0889)	-0.0534	(0.0903)	0.0431	(0.1060)	0.0438	(0.1049)
	pop. density	-0.0019	(0.0018)	-0.0033*	(0.0018)	-0.0011	(0.0021)	-0.0020	(0.0021)
	recreational area (per capita)	0.0267	(0.0212)	0.0192	(0.0217)	-0.0157	(0.0274)	-0.0207	(0.0271)
	public services	0.0095	(0.0396)	-0.0117	(0.0413)	0.0878*	(0.0465)	0.0741	(0.0467)
	unemployment rate (π_{UO})	-0.7235	(0.5140)	-0.5439	(0.5328)	-0.6280	(0.6328)	-0.4840	(0.6320)
relative income control (w_0)		✓		✓		✓		✓	
constant		✓		✓		✓		✓	
observations		1842		1842		1842		1842	
df (model)		46		42		46		42	
F-statistic		8.67		7.61		3.50		3.46	
prob > F		0.0000		0.0000		0.0000		0.0000	
R-squared		0.1778		0.1307		0.1048		0.0878	
adjusted R-squared		0.1567		0.1104		0.0819		0.0665	

*** p<0.01, ** p<0.05, * p<0.1

Note: Statistical inference relies on robust standard errors. For each scenario, the first results also include sensitivity check (A). Measures of behavioural control (θ_R) and migration intention (θ_M) refer to an interstate move.

Table A6.10: Model comparison for sensitivity check (B) – labour market readiness in cross-border migration scenarios

dependent variable		Δ_{A2} (cross-border, given alternative job)				Δ_{U2} (cross-border, given unemployment)			
estimation method		OLS				OLS			
		coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.
gender (female=1)		-3.4902	(3.6870)	-6.2143*	(3.7529)	1.3174	(3.4340)	-0.8155	(3.4557)
age		-0.5850	(1.0043)	-0.4676	(1.0710)	-0.1009	(1.0519)	0.0448	(1.0938)
partnership (yes=1)		3.8026	(3.2903)	6.4245*	(3.3635)	6.0763**	(3.0298)	8.1716***	(3.0505)
language skills (English)									
	high	-9.6019	(6.0418)	-14.4559**	(6.0786)	-4.1462	(5.4643)	-7.8540	(5.4850)
	medium	-5.6319	(5.8209)	-8.4778	(5.8381)	-3.1228	(5.1508)	-5.5875	(5.1463)
risk attitude	score $< \mu - \sigma$	5.4363	(3.9837)	7.6190*	(4.0502)	2.3553	(3.6717)	4.1920	(3.7041)
(career domain)	score $> \mu + \sigma$	8.1725	(5.9830)	6.7934	(6.0731)	1.0579	(4.5199)	0.2183	(4.6857)
patience	score $< \mu - \sigma$	6.4925	(4.8257)	8.6734*	(5.0551)	5.9101	(4.5710)	7.7557	(4.7281)
	score $> \mu + \sigma$	-1.0204	(4.3429)	-2.8971	(4.5968)	-3.5710	(3.8991)	-4.5107	(4.0067)
extraversion	score $< \mu - \sigma$	4.3457	(6.1023)	5.2899	(6.2068)	-6.9805	(5.1088)	-6.3116	(5.1435)
	score $> \mu + \sigma$	3.6434	(4.3038)	1.7437	(4.4425)	6.1615	(3.7518)	4.7124	(3.8558)
neuroticism	score $< \mu - \sigma$	2.4484	(6.0783)	2.7479	(6.3760)	-1.2381	(4.7235)	-0.8940	(4.9103)
	score $> \mu + \sigma$	-6.2936	(4.1521)	-5.1462	(4.2626)	-2.0645	(4.0214)	-1.0120	(4.0789)
openness	score $< \mu - \sigma$	-5.4874	(4.3645)	-4.4288	(4.3895)	-1.0962	(4.1372)	-0.3231	(4.1669)
	score $> \mu + \sigma$	0.5690	(4.3831)	-0.6919	(4.5153)	1.7852	(3.9771)	0.8498	(4.0519)
conscientious-ness	score $< \mu - \sigma$	-3.2504	(5.4554)	-2.5874	(5.6300)	0.5172	(5.1396)	1.3782	(5.2081)
	score $> \mu + \sigma$	-3.6841	(4.2024)	-3.7332	(4.3125)	-4.8903	(3.7622)	-4.3953	(3.8518)
agreeableness	score $< \mu - \sigma$	-0.0822	(4.2569)	-0.0323	(4.3821)	1.3940	(3.8710)	1.5270	(3.9873)
	score $> \mu + \sigma$	1.8612	(4.2906)	1.5964	(4.4058)	-1.0429	(3.8207)	-0.8971	(3.8844)
adaptability	score $< \mu - \sigma$	7.4595*	(4.4453)	9.3735**	(4.5220)	9.2487**	(4.1713)	10.8263**	(4.2131)
	score $> \mu + \sigma$	-0.4943	(5.7680)	-2.9513	(5.6835)	-1.5754	(4.0882)	-2.4940	(4.0468)
importance of	score $< \mu - \sigma$	-1.5890	(4.7466)	-5.0344	(4.7526)	-0.9137	(3.8640)	-3.4724	(3.8729)
prox. (family)	score $> \mu + \sigma$	14.6378***	(5.3718)	18.5556***	(5.5190)	8.0691	(5.2867)	11.6196**	(5.3860)
importance of	score $< \mu - \sigma$	-9.6529**	(4.6209)	-12.0531**	(4.7829)	-7.4114*	(4.0018)	-9.0191**	(4.0359)
prox. (friends)	score $> \mu + \sigma$	9.7200*	(5.8713)	14.3599**	(6.0302)	10.3407*	(5.7908)	14.1385**	(5.9189)
riskiness of move (θ_R)									
	score $< \mu - \sigma$	-14.4254***	(4.3129)			-7.2598*	(3.9699)		
	score $> \mu + \sigma$	5.0434	(6.1948)			8.4333	(6.3899)		
likelihood of move (θ_M)									
	score $< \mu - \sigma$	32.5247***	(5.7197)			27.4024***	(5.2767)		
	score $> \mu + \sigma$	-19.4019***	(3.3769)			-12.5646***	(3.0153)		
work experience									
	part-time (or mini-job)	6.9247*	(4.1476)	7.1514*	(4.2909)	1.3333	(3.8251)	1.2150	(3.9245)
	full-time	-2.2931	(5.7241)	-1.9378	(5.8799)	-2.2182	(5.6495)	-2.2784	(5.7465)
vocational training (yes=1)		-2.0441	(6.0556)	1.4323	(6.4292)	2.8146	(6.0892)	5.2612	(6.3306)
master student (yes=1)		-8.1120	(7.5751)	-10.8781	(8.4404)	-7.9741	(6.8655)	-10.3000	(7.2061)
previous mobility experiences (χ)									
	residential move (yes=1)	2.3415	(3.8985)	1.1510	(3.9582)	2.0574	(3.5237)	1.5347	(3.5452)
	exchange participation (yes=1)	-6.3147*	(3.4325)	-8.0249**	(3.4848)	-2.1373	(3.1621)	-3.5053	(3.2020)
	stay abroad (yes=1)	-10.6642***	(3.7432)	-16.4121***	(3.9011)	-12.4858***	(3.2037)	-16.6608***	(3.3010)
	educational mobility (km)	-0.0410**	(0.0165)	-0.0528***	(0.0169)	-0.0357***	(0.0138)	-0.0443***	(0.0141)
local conditions at origin (a_O)									
	GDP (per capita)	-1.4338***	(0.5510)	-1.4769***	(0.5690)	-1.2177**	(0.4903)	-1.2571**	(0.5119)
	building land prices	0.1732**	(0.0807)	0.1671**	(0.0821)	0.0711	(0.0753)	0.0636	(0.0769)
	accessibility (train)	-0.2824**	(0.1373)	-0.2774**	(0.1385)	-0.2973**	(0.1296)	-0.3007**	(0.1294)
	accessibility (car)	0.0715	(0.2715)	0.0646	(0.2754)	0.0419	(0.2536)	0.0364	(0.2550)
	pop. density	-0.0015	(0.0061)	-0.0031	(0.0062)	0.0010	(0.0057)	-0.0002	(0.0058)
	recreational area (per capita)	0.1402**	(0.0676)	0.1128	(0.0694)	0.1180*	(0.0689)	0.0972	(0.0704)
	public services	-0.0063	(0.1243)	0.0013	(0.1273)	0.0904	(0.1093)	0.0975	(0.1108)
	unemployment rate (π_{UO})	-3.2907*	(1.7198)	-2.9295*	(1.7770)	-3.1447*	(1.6705)	-2.9265*	(1.7055)
relative income control (w_0)		✓		✓		✓		✓	
constant		✓		✓		✓		✓	
observations		1842		1842		1842		1842	
df (model)		46		42		46		42	
F-statistic		8.34		6.66		6.67		5.96	
prob > F		0.0000		0.0000		0.0000		0.0000	
R-squared		0.1586		0.1105		0.1451		0.1076	
adjusted R-squared		0.1370		0.0898		0.1232		0.0868	

*** p<0.01, ** p<0.05, * p<0.1

Note: Statistical inference relies on robust standard errors. For each scenario, the first results also include sensitivity check (A). Measures of behavioural control (θ_R) and migration intention (θ_M) refer to a cross-border move.

Table A6.11: Sensitivity check (C) – gender-specific internal mobility premiums

dependent variable		Δ_{A1} (internal, given alternative job)					Δ_{U1} (internal, given unemployment)				
estimation method		OLS					OLS				
		female		male		$\beta^f = \beta^m$	female		male		$\beta^f = \beta^m$
		coeff.	s.e.	coeff.	s.e.	P>χ^2	coeff.	s.e.	coeff.	s.e.	P>χ^2
age		0.0913	(0.4770)	0.2950	(0.4881)	0.7598	0.8565	(0.5916)	0.9931*	(0.5697)	0.8647
partnership (yes=1)		3.5993*	(1.8667)	0.3097	(1.5398)	0.1635	3.4444	(2.1017)	1.1681	(1.6885)	0.3868
language skills (English)											
	high	-0.9259	(3.4229)	1.8875	(2.3372)	0.4863	1.2531	(3.6961)	1.0432	(2.8668)	0.9633
	medium	-2.2848	(3.1243)	0.2062	(2.0894)	0.4967	-2.3470	(3.4846)	0.5643	(2.4784)	0.4851
risk attitude	score $< \mu - \sigma$	1.2159	(2.1167)	0.3296	(2.0512)	0.7581	-1.9985	(2.3273)	-0.1464	(2.2001)	0.5536
(career domain)	score $> \mu + \sigma$	1.2983	(2.8251)	1.5594	(2.3598)	0.9421	-2.8839	(3.5683)	1.1451	(2.5707)	0.3475
patience	score $< \mu - \sigma$	4.5218*	(2.6099)	3.3283	(2.2075)	0.7205	6.1572**	(3.1099)	0.3495	(2.3345)	0.1257
	score $> \mu + \sigma$	-0.7772	(2.9824)	-0.6331	(1.8569)	0.9664	-2.6610	(3.0105)	-2.3160	(2.2809)	0.9254
extraversion	score $< \mu - \sigma$	1.7577	(3.4660)	3.6845	(2.2727)	0.6335	-3.7468	(3.8057)	-1.4096	(2.7883)	0.6115
	score $> \mu + \sigma$	1.0637	(2.5240)	-0.6828	(1.8701)	0.5687	3.2895	(2.9104)	0.3727	(2.2827)	0.4189
neuroticism	score $< \mu - \sigma$	-2.1022	(4.0218)	-0.9455	(2.1007)	0.7936	-0.3922	(4.6852)	-0.4795	(2.3042)	0.9863
	score $> \mu + \sigma$	-0.1824	(2.1353)	4.2341	(2.9835)	0.2183	1.6790	(2.4592)	1.8294	(3.0525)	0.9687
openness	score $< \mu - \sigma$	-2.4113	(2.5916)	-3.4539*	(1.7853)	0.7340	0.1586	(3.1457)	-2.6665	(2.0488)	0.4402
	score $> \mu + \sigma$	-1.7053	(2.2904)	-4.7221**	(2.0092)	0.3103	3.3074	(2.6023)	-3.6747	(2.2915)	0.0391
conscientious-	score $< \mu - \sigma$	5.9828	(4.3581)	-2.1883	(1.9123)	0.0779	8.2491	(5.4745)	-1.6344	(2.3337)	0.0881
ness	score $> \mu + \sigma$	-2.5667	(2.0580)	2.8553	(2.7548)	0.1068	-2.0255	(2.2753)	-1.5712	(3.0529)	0.9028
agreeableness	score $< \mu - \sigma$	-0.5827	(2.4129)	0.5953	(1.9726)	0.6985	3.2320	(2.9341)	-0.7395	(2.2040)	0.2672
	score $> \mu + \sigma$	3.1164	(2.3309)	2.4393	(2.3548)	0.8342	3.0138	(2.5971)	2.1989	(2.3203)	0.8105
adaptability	score $< \mu - \sigma$	6.3171**	(2.5808)	0.2480	(2.1076)	0.0619	4.1469	(2.8045)	2.7535	(2.4691)	0.7024
	score $> \mu + \sigma$	0.2440	(2.8349)	2.0602	(2.3552)	0.6135	3.3290	(3.1251)	-0.8338	(2.3568)	0.2756
importance of	score $< \mu - \sigma$	3.8032	(2.7288)	-4.4367**	(1.8291)	0.0101	1.7016	(3.4446)	-1.4157	(1.9687)	0.4201
prox. (family)	score $> \mu + \sigma$	9.1731***	(3.0177)	4.2465	(2.9383)	0.2309	2.5875	(3.3010)	-3.0457	(3.3699)	0.2214
importance of	score $< \mu - \sigma$	-4.2766	(2.8834)	-6.1097***	(2.0491)	0.5951	-3.0088	(3.3719)	-3.1250	(2.2345)	0.9765
prox. (friends)	score $> \mu + \sigma$	4.4140	(3.1487)	7.6516***	(2.8363)	0.4338	4.6680	(3.6737)	7.1812**	(3.2864)	0.6014
work experience											
	part-time (or mini-job)	-0.9550	(2.3681)	3.2963*	(1.8203)	0.1445	-1.3855	(2.5171)	1.0500	(2.1885)	0.4544
	full-time	-1.3793	(3.2130)	0.3296	(2.2946)	0.6572	-1.7739	(3.9340)	-4.5735	(2.9519)	0.5595
vocational training (yes=1)		-4.2653	(3.2696)	1.7668	(2.5857)	0.1380	-2.3946	(4.1304)	6.9235**	(3.0284)	0.0621
master student (yes=1)		-10.6519***	(3.6148)	-10.8998**	(4.2983)	0.9640	-11.3440**	(4.5023)	-9.1346	(5.7875)	0.7579
previous mobility experiences (χ)											
	residential move (yes=1)	2.9194	(2.3653)	-1.4666	(1.5523)	0.1118	-0.8413	(2.5342)	-0.9163	(1.9847)	0.9809
	exchange participation (yes=1)	-2.9861	(1.9277)	-2.4073	(1.7649)	0.8205	-2.2940	(2.2806)	-0.8385	(1.8467)	0.6112
	stay abroad (yes=1)	-2.4712	(2.1910)	-6.0446***	(2.1837)	0.2368	-3.2144	(2.4553)	-4.1802*	(2.1985)	0.7640
	educational mobility (km)	-0.0395***	(0.0097)	-0.0129*	(0.0074)	0.0251	-0.0373***	(0.0108)	-0.0168**	(0.0074)	0.1096
local conditions at origin (a_O)											
	GDP (per capita)	-0.0149	(0.2903)	-0.6912***	(0.2567)	0.0737	0.0608	(0.3637)	-0.6243**	(0.2737)	0.1228
	building land prices	0.0734*	(0.0416)	0.0937**	(0.0380)	0.7123	-0.0262	(0.0534)	0.0511	(0.0397)	0.2336
	accessibility (train)	0.0344	(0.0661)	-0.1705**	(0.0735)	0.0340	0.0315	(0.0898)	-0.1510**	(0.0726)	0.1054
	accessibility (car)	-0.0992	(0.1241)	-0.0293	(0.1306)	0.6913	-0.1910	(0.1596)	0.2175	(0.1329)	0.0439
	pop. density	-0.0052*	(0.0027)	-0.0021	(0.0025)	0.3964	-0.0061*	(0.0034)	0.0003	(0.0027)	0.1335
	recreational area (per capita)	-0.0142	(0.0298)	0.0452	(0.0308)	0.1558	-0.0592	(0.0414)	0.0014	(0.0332)	0.2414
	public services	-0.0025	(0.0617)	-0.0235	(0.0572)	0.7981	0.1102	(0.0719)	0.0413	(0.0628)	0.4593
	unemployment rate (π_{UO})	1.2086	(0.8075)	-1.7867***	(0.6824)	0.0037	0.3500	(0.9566)	-0.8518	(0.8529)	0.3367
relative income control (w_0)		✓		✓			✓		✓		
constant		✓		✓			✓		✓		
observations		767		1075			767		1075		
df (model)		41		41			41		41		
F-statistic		4.40		5.09			2.76		2.18		
prob > F		0.0000		0.0000			0.0000		0.0000		
R-squared		0.1703		0.1485			0.1271		0.0854		
adjusted R-squared		0.1234		0.1147			0.0777		0.0491		

*** p<0.01, ** p<0.05, * p<0.1

Note: Heteroscedasticity robust standard errors implemented. The column labelled $\beta^f = \beta^m$ reports p-values from a Wald test (unadjusted) of equality of coefficients between the groups of male and female respondents. This test was implemented using the suest-command in Stata 14.2.

Table A6.12: Sensitivity check (C) – gender-specific cross-border mobility premiums

dependent variable		Δ_{A2} (cross-border, given alternative job)					Δ_{U2} (cross-border, given unemployment)				
estimation method		OLS					OLS				
		female		male		$\beta^f = \beta^m$	female		male		$\beta^f = \beta^m$
		coeff.	s.e.	coeff.	s.e.	P>χ^2	coeff.	s.e.	coeff.	s.e.	P>χ^2
age		0.7754	(1.5313)	-0.8212	(1.4453)	0.4373	1.3404	(1.3506)	-0.3009	(1.4776)	0.4013
partnership (yes=1)		14.7602***	(5.0081)	0.7965	(4.6253)	0.0359	14.7615***	(4.5929)	4.4477	(4.0270)	0.0836
language skills (English)											
	high	-18.3529*	(9.6847)	-11.5501	(7.9025)	0.5770	-5.2503	(8.3719)	-11.0164	(7.3809)	0.5966
	medium	-13.5591	(9.2560)	-4.7200	(7.5466)	0.4481	-5.2779	(7.9089)	-6.2560	(6.8223)	0.9236
risk attitude	score $< \mu - \sigma$	1.5223	(5.4440)	12.8202**	(5.8598)	0.1482	-3.6638	(4.8573)	11.1651**	(5.4248)	0.0371
(career domain)	score $> \mu + \sigma$	-8.6406	(6.6723)	14.3817*	(8.5104)	0.0294	-8.6650	(6.6698)	4.4928	(6.2241)	0.1396
patience	score $< \mu - \sigma$	12.0098*	(6.8866)	7.2494	(7.1059)	0.6223	8.0927	(6.4449)	7.6661	(6.6206)	0.9623
	score $> \mu + \sigma$	5.5605	(7.4683)	-7.8426	(5.9783)	0.1510	4.3846	(7.0028)	-10.3619**	(4.7976)	0.0748
extraversion	score $< \mu - \sigma$	-0.7523	(9.4279)	9.5193	(8.1907)	0.3994	-17.3264**	(8.2332)	-0.3823	(6.4147)	0.0961
	score $> \mu + \sigma$	12.5634*	(6.5351)	-4.1233	(6.1329)	0.0565	12.8215**	(5.7432)	-0.1289	(5.0096)	0.0817
neuroticism	score $< \mu - \sigma$	-9.0318	(9.5209)	5.4118	(7.6901)	0.2264	-2.8313	(8.6624)	-0.6519	(5.9714)	0.8318
	score $> \mu + \sigma$	-5.7465	(5.2416)	-0.2971	(7.1771)	0.5306	3.6059	(5.1946)	-4.5431	(6.7203)	0.3264
openness	score $< \mu - \sigma$	-0.6158	(7.2387)	-5.0324	(5.3558)	0.6150	4.2014	(7.1827)	-3.2592	(5.0298)	0.3829
	score $> \mu + \sigma$	-3.7865	(5.8413)	-1.9528	(6.7934)	0.8341	2.5047	(5.0971)	-4.2963	(6.0612)	0.3795
conscientious-	score $< \mu - \sigma$	21.7379*	(11.6933)	-10.3609	(6.5074)	0.0138	26.0752**	(11.4639)	-6.5270	(5.6796)	0.0089
ness	score $> \mu + \sigma$	-7.3443	(5.1541)	0.8823	(7.4516)	0.3532	-5.9896	(4.8016)	-3.4280	(6.5280)	0.7465
agreeableness	score $< \mu - \sigma$	2.7697	(6.9269)	-0.5193	(5.4937)	0.7030	5.6654	(6.2305)	0.2270	(5.1604)	0.4909
	score $> \mu + \sigma$	-2.5071	(5.6842)	1.8753	(6.8398)	0.6141	-8.2180*	(4.7677)	4.0288	(6.1234)	0.1064
adaptability	score $< \mu - \sigma$	16.6477**	(6.7073)	0.9420	(6.2849)	0.0801	14.4848**	(6.0012)	6.3902	(5.8273)	0.3217
	score $> \mu + \sigma$	-11.2024	(6.9553)	4.0962	(8.4368)	0.1522	-7.1047	(6.0970)	2.7820	(5.5608)	0.2197
importance of	score $< \mu - \sigma$	7.6376	(6.6676)	-10.8201*	(6.1842)	0.0376	5.8985	(7.0214)	-6.9936	(4.5781)	0.1146
prox. (family)	score $> \mu + \sigma$	23.8564***	(7.5691)	16.4875**	(7.9314)	0.4914	14.3435**	(7.1560)	10.5493	(7.9890)	0.7173
importance of	score $< \mu - \sigma$	-10.0261	(6.7155)	-14.9018**	(7.0059)	0.6070	-8.6126	(6.6154)	-9.6679*	(5.4844)	0.8998
prox. (friends)	score $> \mu + \sigma$	4.7737	(8.0912)	21.9748***	(8.4552)	0.1324	10.5356	(7.8705)	17.3203**	(8.1459)	0.5397
work experience											
	part-time (or mini-job)	2.3134	(5.8245)	10.0872	(6.2467)	0.3514	-1.9504	(5.4258)	2.1673	(5.5869)	0.5883
	full-time	-0.7474	(9.4447)	-0.7943	(7.6031)	0.9968	-0.8081	(9.5771)	-2.8821	(7.1977)	0.8591
vocational training (yes=1)		-16.0069	(10.0226)	8.1306	(8.5153)	0.0600	-13.9234	(10.0707)	13.9895*	(8.2709)	0.0282
master student (yes=1)		-20.6427*	(10.7981)	-16.5313	(11.5492)	0.7901	-19.1872**	(9.0208)	-16.1517	(10.1507)	0.8190
previous mobility experiences (χ)											
	residential move (yes=1)	8.5249	(6.4026)	-5.7771	(5.1772)	0.0750	4.9967	(5.7511)	-3.0199	(4.5715)	0.2634
	exchange participation (yes=1)	-8.9818*	(4.9313)	-7.2882	(5.0101)	0.8052	-4.1327	(4.7123)	-3.9050	(4.4388)	0.9713
	stay abroad (yes=1)	-8.6674	(5.7574)	-23.4015***	(5.3578)	0.0550	-14.0606***	(4.6715)	-18.5111***	(4.5949)	0.4867
	educational mobility (km)	-0.0890***	(0.0249)	-0.0274	(0.0215)	0.0549	-0.0957***	(0.0205)	-0.0193	(0.0183)	0.0044
local conditions at origin (a_O)											
	GDP (per capita)	-0.5796	(0.9360)	-1.9333**	(0.7495)	0.2472	-0.9803	(0.9105)	-1.3387**	(0.6510)	0.7426
	building land prices	0.2523**	(0.1203)	0.1189	(0.1127)	0.4072	0.1444	(0.1168)	0.0242	(0.1020)	0.4270
	accessibility (train)	-0.0948	(0.1858)	-0.4010*	(0.2070)	0.2597	-0.1610	(0.1807)	-0.4150**	(0.1850)	0.3143
	accessibility (car)	0.3308	(0.3371)	-0.1597	(0.4131)	0.3466	-0.2477	(0.3205)	0.2775	(0.3703)	0.2725
	pop. density	-0.0067	(0.0084)	-0.0021	(0.0088)	0.7032	-0.0121	(0.0083)	0.0063	(0.0078)	0.0999
	recreational area (per capita)	0.1060	(0.1019)	0.1220	(0.0936)	0.9056	0.1227	(0.1029)	0.0767	(0.0916)	0.7321
	public services	-0.1201	(0.1789)	0.0641	(0.1775)	0.4544	0.1427	(0.1571)	0.0518	(0.1546)	0.6731
	unemployment rate (π_{UO})	0.3495	(2.3984)	-5.0875**	(2.4896)	0.1073	-0.8469	(2.3685)	-4.1676*	(2.3947)	0.3127
relative income control (w_0)		✓		✓			✓		✓		
constant		✓		✓			✓		✓		
observations		767		1075			767		1075		
df (model)		41		41			41		41		
F-statistic		3.98		4.46			3.89		4.08		
prob > F		0.0000		0.0000			0.0000		0.0000		
R-squared		0.1786		0.1206			0.1941		0.1084		
adjusted R-squared		0.1322		0.0857			0.1485		0.0730		

*** p<0.01, ** p<0.05, * p<0.1

Note: Heteroscedasticity robust standard errors implemented. The column labelled $\beta^f = \beta^m$ reports p-values from a Wald test (unadjusted) of equality of coefficients between the groups of male and female respondents. This test was implemented using the suest-command in Stata 14.2.