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To the members of my family...

...with two feet and four paws.

This work is dedicated to my family, who has always supported me and encouraged me to continue.

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Abstract

This dissertation addresses differences in characteristics of individuals and resulting inequalities in the labour market. This is a broad field which is why the chapters of this thesis cover quite diverse aspects of it: on a micro-level, I analyse differences of fixed-term contract workers as opposed to permanent contract workers in a descriptive analysis in chapter 2 before I turn to gender inequalities in contract duration evaluating a parental leave reform in Germany in chapter 3. On a macro-level, I analyse (co-authored with Patrick A. Puhani) differences in the labour mobility across Indian states and districts induced by labour market shocks in chapter 4.

The first analysis addresses the question, which characteristics of employees are related to fixed-term employment. Fixed-term employment compared to permanent employment yields different working conditions, which are not always advantageous for employees, although an increased flexibility might be beneficial for employers. Applying machine learning techniques (LASSO, Elastic Net, and variations), I find that these models considerably increase the predictive power compared to benchmark models including control variables usually used in literature. The selection models make use of the rich information in the SOEP data and identify a variety of control variables that have been mostly neglected in literature so far. The applied variation of a LASSO regression (Double Selection LASSO) shows that this negligence leads to an omitted variable bias in the tested benchmark models and results let conclude that models should be more complex when analysing fixed-term employment to account for the broad variety of individual differences. I show that the results are robust across methods and reveal heterogeneity of the estimates by subgroups.

Focussing on gender related differences in contract duration only a part of the differences can be explained by child-related leaves and the resulting lower labour market experience of women. My results for Germany indicate that it is enough to be a *potential* mother without any child-related career breaks to increase the probability of being employed on a fixed-term basis rather than permanently. To identify the causal effects, I apply a difference-in-differences approach using a change in the legal regulations about parental benefits in Germany in 2007 as natural experiment. I find that women of childbearing age are significantly more likely than men to be employed on a fixed-term basis after the reform. The effect is more pronounced for young women without children indicating an employer-sided discrimination of potential mothers.

On a macro-level, an analysis of (labour) mobility across Indian states and districts covers geographical aspects of labour market differences. The chapter analyses how labour market shocks - measured by changes in non-employment rates, unemployment rates, and wages in fixed-effects regressions - affect regional migration. Comparing the results with those for the United States and the European Union, the most striking difference is that, in India, we do not find significant reactions to asymmetric non-employment shocks at the state level, only at the district level, whereas the estimates are statistically significant and of similar size for the state/NUTS-1 and district level in both the United States and Europe.

Keywords: Model Selection; Industry Characteristics; Occupation; Gender Inequality; Contract Duration; Migration; Regional Convergence; Non-Employment, Unemployment; Wages

Zusammenfassung

In dieser Dissertation werden Unterschiede von individuellen Charakteristika und daraus resultierende Ungleichheiten auf dem Arbeitsmarkt analysiert. Da dies ein weites Feld ist, behandeln die verschiedenen Kapitel dieser Arbeit unterschiedliche Aspekte davon: Auf der Mikroebene untersuche ich in Kapitel 2 mit einer deskriptiven Analyse die Unterschiede zwischen befristet und unbefristet Beschäftigten, bevor ich mich den geschlechtsspezifischen Ungleichheiten bei der Vertragsdauer in Kapitel 3 zuwende indem ich eine Reform der Elternzeit in Deutschland evaluiere. Auf der Makroebene analysiere ich in Kapitel 4 (in Zusammenarbeit mit Patrick A. Puhani) Unterschiede in der Arbeitsmobilität zwischen indischen Bundesstaaten und Distrikten, die durch Arbeitsmarktschocks verursacht werden.

Die erste Analyse befasst sich mit der Frage, welche Charakteristika in Verbindung mit der Vertragsdauer stehen. Befristete Arbeitsverhältnisse bringen im Vergleich zu unbefristeten unterschiedliche Arbeitsbedingungen mit sich, die für Arbeitnehmer nicht immer von Vorteil sind. Für Arbeitgeber kann deren größere Flexibilität aber vorteilhaft sein. Ergebnisse der Anwendung von Machine Learning Methoden (LASSO, Elastic Net und Variationen davon) zeigen, dass diese Modelle die Vorhersagekraft im Vergleich zu Benchmark-Modellen mit Kontrollvariablen, die in der Literatur üblicherweise verwendet werden, deutlich erhöhen. Die Selektionsmodelle nutzen die umfassenden Informationen der SOEP-Daten und identifizieren eine Vielzahl von Kontrollvariablen, die in der Literatur bisher meist vernachlässigt wurden. Die verwendete Variation einer LASSO-Regression (Double Selection LASSO) zeigt, dass diese Auslassung relevanter Variablen in den getesteten Benchmark-Modellen zu einer Verzerrung der Koeffizienten führt. Die Ergebnisse lassen den Schluss zu, dass die Modelle bei der Analyse befristeter Arbeitsverhältnisse komplexer sein sollten, um die große Vielfalt individueller Unterschiede zu berücksichtigen. Ich zeige, dass die Ergebnisse methodenübergreifend robust sind und eine Heterogenität der Schätzungen nach Untergruppen erkennen lassen.

Wenn man sich auf die geschlechtsspezifischen Unterschiede in der Vertragsdauer konzentriert, kann nur ein Teil davon durch kinderbedingte Abwesenheiten und die daraus resultierende geringere Arbeitsmarkterfahrung von Frauen erklärt werden. Meine Ergebnisse lassen vermuten, dass es in Deutschland ausreicht, eine potenzielle Mutter ohne kinderbedingte Unterbrechung der beruflichen Laufbahn zu sein, um die Wahrscheinlichkeit zu erhöhen, befristet statt unbefristet beschäftigt zu sein. Um die kausalen Effekte zu identifizieren, wende ich

einen Differenz-in-Differenzen-Ansatz an, der eine Änderung der gesetzlichen Regelungen in Deutschland im Jahr 2007 als natürliches Experiment nutzt. Ich finde heraus, dass Frauen im gebärfähigen Alter nach der Reform signifikant häufiger befristet beschäftigt sind als Männer. Der Effekt ist bei jungen Frauen ohne Kinder stärker ausgeprägt, was auf eine arbeitgeberseitige Diskriminierung potenzieller Mütter hindeutet.
Eine Analyse der (Arbeits-)Mobilität auf Makroebene zwischen indischen Bundesstaaten und Distrikten befasst sich mit geografischen Aspekten von Arbeitsmarktunterschieden. In diesem Kapitel wird untersucht, wie Arbeitsmarktschocks - gemessen an Veränderungen der Nichtbeschäftigungsquote, der Arbeitslosenquote und der Löhne in Fixed-Effects-Modellen - die regionale Migration beeinflussen. Vergleicht man die Ergebnisse mit denen für die Vereinigten Staaten und die Europäische Union, so ist der auffälligste Unterschied, dass wir in Indien keine signifikanten Reaktionen auf asymmetrische Nichtbeschäftigungsschocks auf der Ebene der Bundesstaaten, sondern nur auf Distriktebene feststellen, während die Schätzungen sowohl in den Vereinigten Staaten als auch in Europa statistisch signifikant und von ähnlicher Größe für die Ebene der Bundesstaaten/NUTS-1 und der Bezirke sind.

Schlagworte: Modellauswahl; Branchenmerkmale; Berufsfeld; Geschlechterungleichheit; Vertragsdauer; Migration; Regionale Konvergenz; Nicht-Beschäftigung, Arbeitslosigkeit; Löhne

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CHAPTER 1

Introduction

1 Introduction

The topics of this thesis are quite different: on a micro-level, they cover analyses of fixed-term employment in Germany and on the macro-level, the corresponding chapter covers labour mobility in India.[1] Nevertheless, one can subsume the topics under a common term: differences in characteristics of individuals and resulting inequalities on the labour market.[2]

On the micro-level, following standard human capital theory, different characteristics include a dissimilar endowment of individuals with human capital and can, thereupon, lead to differing human capital accumulation incentives (see e.g. Piketty (2015)). This can result in varying labour market outcomes. When looking at differences in workers' individual characteristics, one not only must look at the actions and decisions of these workers (e.g. in terms of job choice, educational choices etc.), but also consider the reaction of other market participants. As Piketty (2015) states, discrimination - to understand as an unequal treatment of individuals - can lead to inefficient allocations if the reason for the discrimination has no relation to the requirement profile of the job. This thesis does not sharply distinct between taste-based and statistical discrimination but refers rather to statistical discrimination as defined by Phelps (1972) and Arrow (1973) in Chapters 2 and 3: are workers treated differently in terms of their contract duration because of ambiguous signals their characteristics provide?

On a macro-level, the difference in characteristics considered in this thesis is the country or region of residence. Labour market conditions are naturally very diverse in different countries. The focus here lies on the potential of different countries to mitigate effects of shocks to the labour market by inner-country migration. The ability to realise the full adjustment potential of countries probably depends on mobility barriers between states and regions of the country, which could be based on language or cultural variety (see e.g. Kone et al. (2018) or Aggarwal et al. (2020)). We analyse labour mobility in India as a developing country and compare our results to results of Jauer et al. (2019) for Europe and the US: do labour market shocks in India lead to a inner-country (labour) migration?[3]

[1] With "micro-level", I refer to analyses using data on an individual level; with "macro-level", I refer to the analysis using data aggregated on regional levels.

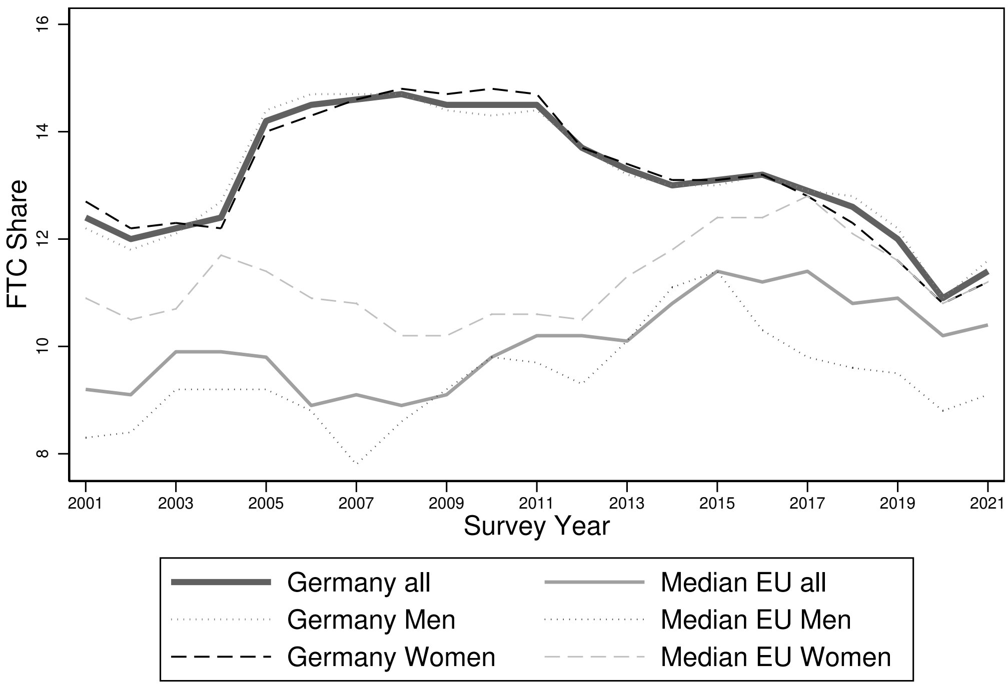
[2] On the macro-level, the differing states/districts of residence is the individual characteristic considered.

[3] This chapter is co-authored with Patrick A. Puhani.

Chapters 2 and 3 analyse different aspects of fixed-term employment in Germany. Fixed-term employment is opposed to permanent employment and describes employment relationships for which contracting parties agree upon a certain time period for the work contract in advance. As those two chapters expose in their corresponding literature reviews, fixed-term employment comes with benefits for employers as it facilitates the adjustment of the workforce to changing labour demand and employers can use fixed-term contracts as a prolonged probation period, but it comes also with disadvantages for employees in terms of lower wages, a higher risk of unemployment, and lower investments in employer provided training, to name just a few.

Figure 1.1 shows the share of temporary employment for Germany compared to the median of the EU27 member states (solid lines) and measures by gender (dashed and dotted lines). The share of temporary workers is higher for Germany compared to the median value of all member states, although the numbers seem to converge. The dashed lines show the measures for women, who seem to build a higher share in temporary employment in the EU27 member states than men. The numbers for Germany by gender seem quite close in this figure. One has to keep in mind that for figure 1.1 all age groups are used and a plot by age groups will grant another picture by gender (see figures 3.2 and 3.3 in chapter 3).

Figure 1.1: Share of Temporary Employment



Data Source: OECD.Stat

In chapter 2, I analyse potential determinants of fixed-term employment in a descriptive analysis to answer the question which characteristics of individuals are linked to fixed-term employment. Using data of the German Socio-Economic Panel (SOEP) for the years 2001-2018, I apply two machine leaning techniques (shrinkage techniques), LASSO (Tibshirani, 1996) and Elastic Net (Zou and Hastie, 2005), to find a model with a high power in predicting the belonging to the class of FTC (fixed-term contract) workers. I find that LASSO performs slightly better in the out-of-sample prediction than Elastic Net and that both techniques outperform the benchmark models that include manually chosen or all available controls. The pure selection models choose a much broader set of control variables than those usually used in literature and increase the sensitivity (true positive rate) of the models from 2.6%-11.5% to about 32%. The benchmark model using all available control variables over-fits the data and performs worse in the out-of-sample prediction. The applied shrinkage techniques include more differentiated measures of the educational attainment and measures about the current employment relationship, like the occupation and the industry, indicating a certain correlation between fixed-term employment and those measures. To compare shrinkage technique coefficients to benchmark model coefficients, I apply a LASSO for inference technique, the Double Selection LASSO (Belloni et al., 2014a). Results show that the coefficients of the benchmark models suffer from omitted variable bias, though they mostly meet expectations about the direction of effects. However, results differ for the working experience: while the unemployment experience seems to correlate with the FTC probability, the working experience shows no significant correlation, which contradicts findings from literature. To analyse whether the controls chosen by the LASSO differ by gender, I run a subgroup analysis. I find that the age, which is usually supposed to have an effect in literature, is not included in the model for men but only for women. Furthermore, my results indicate that the gender-segregation in occupations is linked to the FTC probability: the included occupations and industries differ by gender. Still, the choice of the included occupations and industries do not reflect the share of men and women working in those occupations generally.

Chapter 3 focuses on the gender aspect of fixed-term employment. I analyse whether women of childbearing age are more likely to be employed on a fixed-term basis than men in the same age group. A potential reason could be an employer-sided discrimination of women in this age group. I apply a difference-in-differences approach as identification strategy, using the parental leave reform in Germany in 2007 as natural experiment. This reform increased parental benefits with the intention to boost incentives for having children. I use SOEP data for the years 1995-2016. My results indicate that women of childbearing age more likely than men to be employed on a fixed-term basis and that this effect is even larger for young (and young and married) women without children, i.e. *potential mothers*. Young women are roughly 12% more likely to be employed on a fixed-term basis than men after the reform. The estimate increases to roughly 18% for young women without children. Results of a difference-in-difference-in-differences approach, comparing young women to men and older women, show that this effect is age group related. The results are robust to changes in the definition of the childbearing age and to the test of placebo reforms. The reform of 2007 has set different rates of parental benefits for different income groups. A subgroup analysis by income shows that the effect is driven by the second lowest income group of women without children, which form a major part of observations. An analysis of a sample reduced to only new hires shows equivalent results.

Chapter 4 turns to a macroeconomic view of the labour market and addresses the question if and to what extend labour market shocks lead to migration across Indian states and districts. We proxy migration by the population change in states/districts and define labour market shocks as changes in the unemployment/non-employment rate and as changes in the wage rate (both lagged by two years). Using aggregated data from the National Sample Survey Office of India for the years 2004-2012, we apply a region and time fixed effects regression and compare results to the estimates of Jauer et al. (2019) for the US, EU-27, and Eurozone. We find that there is a migration of Indian workers caused by wage and non-employment shocks. The wage effect is bigger in India than in the US and Europe but the non-employment effect is not significant on the state level. This changes in the analysis of Indian districts: a one percent increase in the non-employment ratio of a region decreases the population growth factor by 12.6%. Results are robust to restricting the sample to individuals aged below 50 and to changes in the considered period.

Chapter 2

"One Way or The Other, I'm Gonna Find You" - Analysing Determinants of Fixed-Term Employment Using LASSO and Elastic Net Regression

2 "One Way or The Other, I‘m Gonna Find You" - Analysing Determinants of Fixed-Term Employment Using LASSO and Elastic Net Regression

2.1 Introduction

The share of fixed-term contract (FTC) workers shows an increasing trend in Germany: it rose from around 10% in 2001 to 12.6% in 2018.[1] This growth of 2.6 p.p. corresponds to around 712,012 individuals (OECD, 2021). As fixed-term contracts are a form of atypical employment and do not have exclusively positive effects on all labour market actors, this increase raises the question which characteristics are associated with being employed on a fixed-term rather than permanent basis.

The aim of this analysis is to find a model that best classifies the belonging to the class of FTC workers. The knowledge about characteristics that drive fixed-term employment is beneficial to all labour market actors: On the labour demand side it might be important for firms to fill vacant positions by identifying workers who are most likely to respond to job offers. On the labour supply side it might be interesting for job seekers to identify characteristics that foster fixed-term or permanent employment depended on preferences about job stability. The German government has to ensure the prevention of misuse of fixed-term employment according to an EU-directive presented below. To know driving characteristics helps to consider whether the current legal regulations regarding fixed-term employment would need to be adapted.

Usually, analyses on fixed-term contracts use control variables manually selected on the basis of domain knowledge. In my analysis, I make use of data driven shrinkage methods to find the models used for prediction. In this chapter I apply the shrinkage techniques LASSO and Elastic Net to find the determinants of fixed-term employment using a complex dataset, the Socio-Economic Panel of Germany (SOEP), including various variables. The contribution of this analysis to the existing literature is the identification of variables that should be considered when it comes to the analysis of fixed-term employment by applying machine learning techniques rather than select models manually. A deeper understanding of the characteristics that are liked to fixed-term employment is important as fixed-term employment affects the demand

[1] Opposed to permanent contract (PC) workers, fixed-term contract (FTC) workers work on a contract with limited duration.

and supply sides of the labour market differently.

To analyse the potential determinants of FTC employment, I apply simple logistic regressions with standard control variables from the literature (varying across four benchmark models), then run LASSO and Elastic Net regressions and compare the predictive performance of the models based on their sensitivity to correctly classify the belonging to the class of FTC workers. To assess the models' performances, I split the sample into a training and validation set. The main results of my analysis is that both shrinkage techniques outperform the benchmark models and that LASSO performs best in predicting the belonging to the class of FTC workers: it raises the sensitivity (true positive rate) from 2.6% (simplest benchmark model) to roughly 32%. This result comes from the fact that the LASSO model presented here uses more differentiated variables, e.g. regarding the educational attainment, job characteristics as the training requirements, the occupation, the occupational position and the industry, as well as differentiated information about the employment history, and thus maps the relationships more accurately than the benchmark models. Additionally, the inclusion of several variables regarding worries about several aspects of life let suggest that there is a correlation to fixed-term employment. The analysis is purely descriptive and endogeneity problems such as e.g. reverse causality are not accounted for (see section 2.4 for a discussion on this aspect). Nevertheless, the shrinkage techniques all provide a larger sensitivity than benchmark models and perform better in the out-of-sample prediction. As a robustness test, I choose a different way of splitting the sample, namely Cross Validation. Furthermore, I apply an adaptive LASSO regression which uses a different way of selecting the tuning parameter. Results are robust to these changes.

To provide insights on the controls usually used in literature, I apply a "LASSO for inference model", namely a double selection logistic LASSO (Belloni et al., 2014a).[2] Results indicate that expectations about the direction of the effect of usual controls on the FTC probability are mostly met. Only for the working experience the results differ from expectations: it does not have a significant effect in the double selection model. Furthermore, most coefficients in the simple logistic model using only standard controls are probably at least partially biased caused by omitted variables. To account for potential gender differences I apply the LASSO separately for men and women and find that some of the included variables differ by gender. Especially in occupations and industries, I find differences which cannot be fully explained by the occupational/industrial gender-segregation.

[2] At this point, I must clarify that I am not claiming causal inference with this analysis. See the related discussion in section 2.4.

To clarify why it is important to analyse potential determinants of FTCs, one has to look at effects of FTCs on the different labour market actors. Fixed-term employment comes with different effects for employers and employees. First, it increases flexibility for employers which might cause a higher rate of job creation, although evidence in literature for this aspect is mixed. Second, it can provide a bridge to permanent employment but there is evidence in literature for creating a trap at least for some groups of workers as well. Third, it yields several disadvantages for employees compared to permanent employment and is therefore worth a closer look.

Considering the demand side, analyses from the related literature show that positive aspects of fixed-term contracts for employers are an increased flexibility, the option of a longer probation period, and higher employee effort (e.g. Eichhorst (2014), Engellandt and Riphahn (2005)). An increased flexibility for employers is important if they have to adjust their workforce according to changes in the labour demand and allows potentially saving cost from dismissals: if the contract is not renewed, the employment relationship ends when an FTC expires. This offers an advantage for employers especially in countries with a strict employment protection legislation on permanent contracts. Second, with fixed-term contracts employers can prolong the probation period which is advantageous in the case of uncertain signals of employees.[3] If the employer wants to test the employee for more than six months, an FTC is a way to circumvent dismissal costs. Third, findings from the literature show that FTC workers provide higher effort by a higher supply of overtime hours (Engellandt and Riphahn (2005) for Swiss; Bossler and Grunau (2019) for Germany). If firms know which individual characteristics drive fixed-term employment, they can design their job offers accordingly and attract exactly the workers they are searching for.

Even if there are positive effects from FTC employment for employers, it is not the all-in-one device suitable for every purpose and yields no guarantee for more stable matches: whether the use of a longer probation period through FTCs leads to a better match quality or more stable matches seems to depend highly on the legal regulations of different countries. While Boockmann and Hagen (2008) find for Germany that employment relationships starting on an FTC are as stable as those starting on a PC, results from other literature show that FTCs do not lead to a lower unemployment ratio, which would indicate that the number of matches using FTCs ad-

[3]During the probation period it is possible to agree upon a shorter notice period: according to §622 (1) of the German Civil Code (*Bürgerliches Gesetzbuch*, BGB) the notice period is four weeks. During the first six months of an employment relationship, contracting parties can agree upon a shorter notice period of two weeks (§622 (3) BGB). Disregarding the contract type, the protection against dismissal takes effect after six moths in Germany and a shorter notice period than four weeks is not possible any more.

ditionally to PCs is not higher (see e.g. Blanchard and Landier (2002) for France, Kahn (2010) for 9 European countries[4], and Cahuc and Postel-Vinay (2002) for theoretical considerations). Turning to the labour supply side, another strand of literature on FTCs concentrates on the question whether FTCs are rather a "bridge" to permanent employment or a "trap" for employees, i.e. whether the stepping stone hypothesis or the dead-end hypothesis holds.[5] Again, results differ by countries. Filomena and Picchio (2021) provide a meta-analysis and find that the majority of considered analyses show evidence for the dead-end hypothesis (45%), whereas 32% support the steeping stone hypothesis, and 23% of papers find mixed results (Filomena and Picchio (2021), p.5). Besides the legal regulations in different countries, results from literature let suggest that it depends on the outside options of employees, and therefore on the education and (negative) signals, whether FTCs are rather a bridge or a trap.[6]

Consequences of a fixed-term employment for employees are besides others that FTC workers receive less training, have a lower job satisfaction, face a higher unemployment risk, and receive lower wages. Arulampalam et al. (2004) find for five European countries (Austria, Britain, Denmark, Finland, and Spain) that men in fixed-term contracts receive less employer provided training. The results for women in their analysis are mixed and depend on the country. Chadi and Hetschko (2016) detect for Germany, that FTC workers have a lower job satisfaction. A wage penalty for fixed-term employment has been found in many analyses for different countries.[7] Besides the stated negative consequences for employees, results from literature indicate that FTC workers have a higher risk of work-related accidents in Spain (Guell and Petrongolo, 2007) and that fixed-term employment leads to a delay of motherhood in Spain (De la Rica and Iza, 2005). The aspects outlined show that FTC workers are mostly disadvantaged compared to

[4] BE, FI, FR, GER, IT, NL, PT, ES, and the UK.

[5] See Eichhorst (2014) for an overview. The stepping stone hypothesis assumes that a fixed-term contract acts as the first contract towards an open-ended contract; the dead-end hypothesis states that one is trapped in repetitive fixed-term contracts.

[6] Guell and Petrongolo (2007) find for Spain that it depends on the outside options of employees, which are linked to education, whether they are trapped in repeated spells of FTCs. Gagliarducci (2005) finds for Italy that it plays an important role whether there have been repeated spells of fixed-term contracts in the past. According to his findings, the tenure rather improves the conversion but repeated spells of FTCs worsens employees' perspectives. This goes in line with the argumentation that repeated spells of FTCs act as negative signals to employers. Berton et al. (2011) finds for Italy, that the conversion probability depends on the type of the temporary contract. They consider fixed-term contracts, training contracts, apprenticeship contracts, and freelance contracts and find that all temporary contracts are an effective way to exit unemployment but yield positive employment prospects rather within a firm than across firms. As this chapter purely concentrates on fixed-term contracts, this aspect is not further considered here.

[7] See e.g. Booth et al. (2002) and Brown and Sessions (2005) for the UK; Schömann and Kruppe (1994), Hagen (2002), and Mertens et al. (2007) for GER; Gash and McGinnity (2007) for GER and FR; Van Lancker (2012) for a higher poverty risk analysing 24 European countries (AT, BE, BG, CZ, EE, GER, ES, FI, FR, EL, HU, IE, IT, LT, LV, NL, NO, PL, PT, SE, SI, SK, and the UK).

PC workers and that their higher risks are not compensated by a risk premium in form of higher wages. Depended on workers preferences about the stated aspects, it can be beneficial for job seekers to know which characteristics drive FTC employment to evaluate whether they should reconsider own choices, e.g. about the educational attainment or job sector or industry.

After providing information about the legal background of fixed-term employment in Germany in section 2.2.1 and a short literature review of determinants of FTCs in section 2.2.2, I present the data and descriptives in section 2.3 and methods used in section 2.4. Section 2.5.1 includes results from the whole sample, section 2.5.2 from robustness tests, and section 2.6 from the statistical inference task (LASSO Double Selection model). Section 2.7 adds results of the subgroup analysis and section 2.9 concludes.

2.2 Background and Literature

2.2.1 Legal Regulations

In this section, I provide a short overview over the legal background of fixed-term contracts and their history in Germany. Legal regulations evolved over the past decades in that the conditions for using a fixed-term contract have been more clearly defined and the allowed number and length of fixed-term contracts changed.[8] In 1960, the regulation on fixed-term contracts was based on a court decision[9] stating that there had to be a factual reason to limit the contract duration. Those factual reasons were determined by jurisdiction. This changed 1985 with the introduction of the Employment Promotion Act 85 (BeschFG, *Beschäftigungsförderungsgesetz*) where additionally to factual reasons, limited contracts without factual reasons were permitted for up to 18 months under two conditions: first, if an employee was newly hired (this was the case if there was no labour contract between employer and employee in the last 4 months); and second, if the contract was directly following an apprenticeship and there was no unlimited position available. Only one fixed-term contract was allowed.[10] In 1996, the period increased from 18 months to 2 years for firms that had existed less than 6 months or had

[8] See Buschmann (2017) for an overview.
[9] BAG 12.10.1960 GS AP Nr.16 zu §620 BGB.
[10] BGBI (1985), Teil I, pp.710ff.

less than 20 employees.[11] In 1999 there was an EU directive[12] to protect employees against misuse of limitations, which was followed by the Part-Time and Fixed-term Employment Act (TzBfG, *Teilzeit- und Befristungsgesetz*) that came into force on January 1th, 2001 and replaced the BeschFG to implement the EU directive. This law is still the current regulation of the use of fixed-term contracts in Germany.[13] Knowing about job or worker characteristics that drive FTC employment can help to evaluate whether the EU directive has been sufficiently implemented.

According to the current Part-Time and Fixed-term Employment Act, fixed-term contracts can be with or without factual reasons. With factual reasons there is no limit on the duration or the consecutive number of fixed-term contracts, which contracting parties can choose freely.[14] Fixed-term contracts without factual reasons are more limited. There are three cases stated in the law in which fixed-term contracts are allowed without a factual reason: first, if the employment is calendared (in German: "kalendermäßig"), contracts are allowed up to 2 years with maximum 3 renewals within this period and if there was no employment relationship between the contracting parties in the past; second, in the first 4 years after company foundation with a limitation up to 4 years; third, if the employee is older than 52 and was unemployed at least 4 month before with a limitation up to 5 years (§14 (2-3) TzBfG).
Summarising, the reform in 1985 made it in general easier to employ on a fixed-term basis. The legislation in 2001 was to ensure to implement the EU-directive to prevent misuse. Since then it is possible, to renew an FTC without factual reasons up to 3 times in the period of 2 years (before, there was one contract allowed in the period of 2 years). Contracts without factual reasons

[11] BGBI (1996), Teil I, pp.1478ff.

[12] "Measures to prevent abuse (clause 5)
1. To prevent abuse arising from the use of successive fixed-term employment contracts or relationships, Member States, after consultation with social partners in accordance with national law, collective agreements or practice, and/or the social partners, shall, where there are no equivalent legal measures to prevent abuse, introduce in a manner which takes account of the needs of specific sectors and/or categories of workers, one or more of the following measures: (a) objective reasons justifying the renewal of such contracts or relationships; (b) the maximum total duration of successive fixed-term employment contracts or relationships; (c) the number of renewals of such contracts or relationships. 2. Member States after consultation with the social partners and/or the social partners shall, where appropriate, determine under what conditions fixed-term employment contracts or relationships: (a) shall be regarded as 'successive' (b) shall be deemed to be contracts or relationships of indefinite duration."
see COUNCIL DIRECTIVE 1999/70/EC of 28 June 1999 concerning the framework agreement on fixed-term work concluded by ETUC, UNICE and CEEP, p. L175/47.

[13] An exception is the German Act on Fixed-Term Scientific Contracts (WissZeitVG, *Wissenschaftszeitvertragsgesetz*), which applies to academic staff.

[14] Factual reasons stated in the law are: the demand for work is temporary, the contract follows directly apprenticeship or university, employment as stand-in, there is a specific nature of the work that requires a fixed-term contract ("Eigenart der Arbeitsleistung"), reasons within the person of the employee justify a time limit ("in der Person des Arbeitsnehmers liegende Gründe rechtfertigen Befristung"), the position is financed from public budgetary funds, or the limitation due to court settlement (§14 (1) TzBfG).

became easier to implement with the new legislation in 2001. Additionally, factual reasons are now explicitly stated in the law. Before the TzBfG they were defined "only" through jurisdiction. With the implementation of this directive, an anti-discrimination paragraph for fixed-term workers was introduced. Whether the law of 2001 made restrictions on the use of FTCs more serve is ambiguous: successive FTCs without factual reasons are allowed, even if the time span did not change and even if the number of renewals is limited; the time span after company foundation was increased; while factual reasons are now defined in the law, their definition is still broad. As effects of the change of the law are unclear I restrict the considered period to 2001-2018 to prevent potential biases from the law change.

2.2.2 Literature

My benchmark models include controls usually used in literature. Therefore, I present results from analyses of control variables in the related literature: Most studies in the related literature concentrate on analysing the same determinants for FTCs, which I group into three categories, personal characteristics, employment history characteristics, and current employment characteristics, in table 2.1. In the related analyses, included determinants differ slightly but results about the direction of the effects of the stated determinants of fixed-term employment are mainly consistent. My analysis contributes to the literature by an extended analysis considering all potential determinants provided in the data.

Table 2.1: Determinants from Selected Literature on Fixed-Term Employment in Germany

	Characteristic	Effect	Source
Personal:			
	Age	(-)	Schömann and Kruppe (1994), Giesecke and Groß (2002), Hagen (2002), and McGinnity et al. (2005)
	Education	mixed	Giesecke and Groß (2002), Hagen (2002), and McGinnity et al. (2005)
	Number of Children	mixed	Hagen (2002), Petrongolo (2004)
	Marital Status	mixed	Hagen (2002), Petrongolo (2004)
	Gender	(∼)	Petrongolo (2004), Giesecke and Groß (2002), Hagen (2002), and McGinnity et al. (2005)
	Nationality	(∼)	Giesecke and Groß (2002) and McGinnity et al. (2005)
Employment History:			
	Working Experience	(-)	Hagen (2002)
	Unemployment Experience	(+)	Giesecke and Groß (2002) and Hagen (2002)
	Dismissal	(∼)	Hagen (2002)
Current Employment:			
	Working in Public Service	(+)	Schömann and Kruppe (1994), Giesecke and Groß (2002), and McGinnity et al. (2005)
	Occupation	mixed	Hagen (2002) and McGinnity et al. (2005)
	Position	(-)	Giesecke and Groß (2002)
	Firm Size	(∼)	Giesecke and Groß (2002) and Hagen (2002)

Notes: (-) describes a negative effect on the probability of being employed on a fixed-term basis with an increase of the stated characteristic, (+) a positive effect, respectively. (∼) describes that no significant effect (or only significant effect for subgroups) has been found in literature whereas "mixed" describes that the effect depends on the categories of the characteristic.

Personal characteristics provide signals for employers about the presumed quality of employees. As FTCs are used as screening mechanism, it is likely that their usage depends on the age of individuals: younger individuals with less labour market experience provide more uncertain signals to employers, which could foster the use of FTCs and is associated with a higher FTC probability for younger age groups (see e.g. Schömann and Kruppe (1994), Giesecke and Groß (2002), Hagen (2002), and McGinnity et al. (2005) for Germany). The relation with education of individuals seems to be non-linear: the FTC probability is higher for low and high educated individuals compared to individuals with an apprenticeship (see e.g. Guell and Petrongolo (2007) Giesecke and Groß (2002), Hagen (2002), and McGinnity et al. (2005)). The number of children and being married do not seem to be significantly related to the probability of being employed on a fixed-term basis in Germany (see Hagen (2002)). Nevertheless, considering other European countries Petrongolo (2004) finds gender differences in the effect of being married on the FTC probability.[15] There seems to be a gender related difference in the probability to be employed on a fixed-term basis that is related to the number of children and the marital status in several European countries. The gender effects are not significant in her analysis in Germany, which is also the case for findings of Giesecke and Groß (2002), Hagen (2002), and McGinnity et al. (2005). Nationality is at best weekly related to the FTC probability (see Giesecke and Groß (2002) and McGinnity et al. (2005)[16]).

Considering the employment history of individuals, the working and the unemployment experience seem to have an impact on the FTC probability: Hagen (2002) finds a significantly decreasing effect for public service employees with increasing experience and Giesecke and Groß (2002) and Hagen (2002) find a positive relation of unemployment experience and FTC probability, which again relates to the signalling function of this measure. Related to negative signals to employers, Hagen (2002) finds also a significantly increasing effect on the FTC probability of having been out of the labour force and having changed the employer. Results for having been dismissed by the former employer were not significant in his analysis (Hagen (2002), pp. 684f).

The third group of characteristics relates to the current employment of individuals. Civil service employees (employees in the public service) have a higher FTC probability (see Schömann and Kruppe (1994), Giesecke and Groß (2002), and McGinnity et al. (2005)). The occupation seems to have an effect as well, though results from literature are not comparable as they use different

[15] Being a single women is associated with a higher FTC probability than men in Sweden, Finland, Belgium, Austria, Ireland, and southern Europe. Married women with no kids are associated with a higher FTC probability in Finland, the Netherlands, Belgium, Ireland, and southern Europe, only Denmark yields a negative correlation for this subgroup. Being married with kids is associated with a higher FTC probability for women than for men in Belgium, Luxembourg, Austria, Ireland, and southern Europe (Petrongolo (2004), pp. 338ff).

[16] Significant effects for job entrants found.

base categories.[17] The firm size is included in some analyses but no significant effects were found (Giesecke and Groß (2002) and Hagen (2002)). Giesecke and Groß (2002) additionally consider the position and find a negative correlation for all levels compared to the lowest, which indicates that the FTC probability decreases with superior positions. Furthermore, they include marginal employment and find a positive effect on the FTC probability.
What is missing in the literature so far is an extended analysis considering all potential determinants. An exception is the analysis of Hagen (2002) who includes a large number of reasonable potential controls and interactions. Nevertheless, there might be additional determinants, like e.g. the industry, that are missing in his analysis. Therefore, my analysis contributes to this strand of literature by providing an analysis considering all potential controls from the SOEP (which is also used by Hagen (2002) and Giesecke and Groß (2002)) using shrinkage techniques and comparing the results with the related literature.

2.3 Data and Descriptives

I use data from the latest wave of the German Socio-Economic Panel (SOEP, v35).[18] I restrict the considered period to the years 2001-2018 because of the above stated changes in legal regulations in earlier years (section 2.2.1) and to employees of working age (20-65) who are not in apprenticeship as their contracts in Germany are usually on a fixed-term basis disregarding their characteristics. Excluding variables containing more than 38,000 missings[19], the final dataset contains observations for 225,484 individuals and 18 years. I split the sample into a training dataset (60%) and a validation dataset (40%) to assess and compare the performance of the applied models.[20] To take advantage of the methods, as many variables as possible should be inserted without too much of a pre-selection but I exclude variables that are not available for all years and those containing income information (potential endogeneity). Due to the computational power restrictions, I exclude further irrelevant and redundant variables (e.g. variables

[17] Hagen (2002) for example finds a negative correlation for clerks using plant machine operators and assemblers as base category, McGinnity et al. (2005) find a positive correlation for professionals using manufacturers as base category and a positive correlation for low skilled white and blue collar workers compared to skilled manual workers.

[18] Socio-Economic Panel (SOEP), data for years 1984-2018, version 35, SOEP, 2019, doi:10.5684/soep.v35. Variables from the datasets pgen (Person-Related Status and Generated Variables), pequiv (CNEF Variables with Extended Income Information), and pl (Data from individual questionnaire in long format) are used.

[19] Corresponds to around 15% missing values.

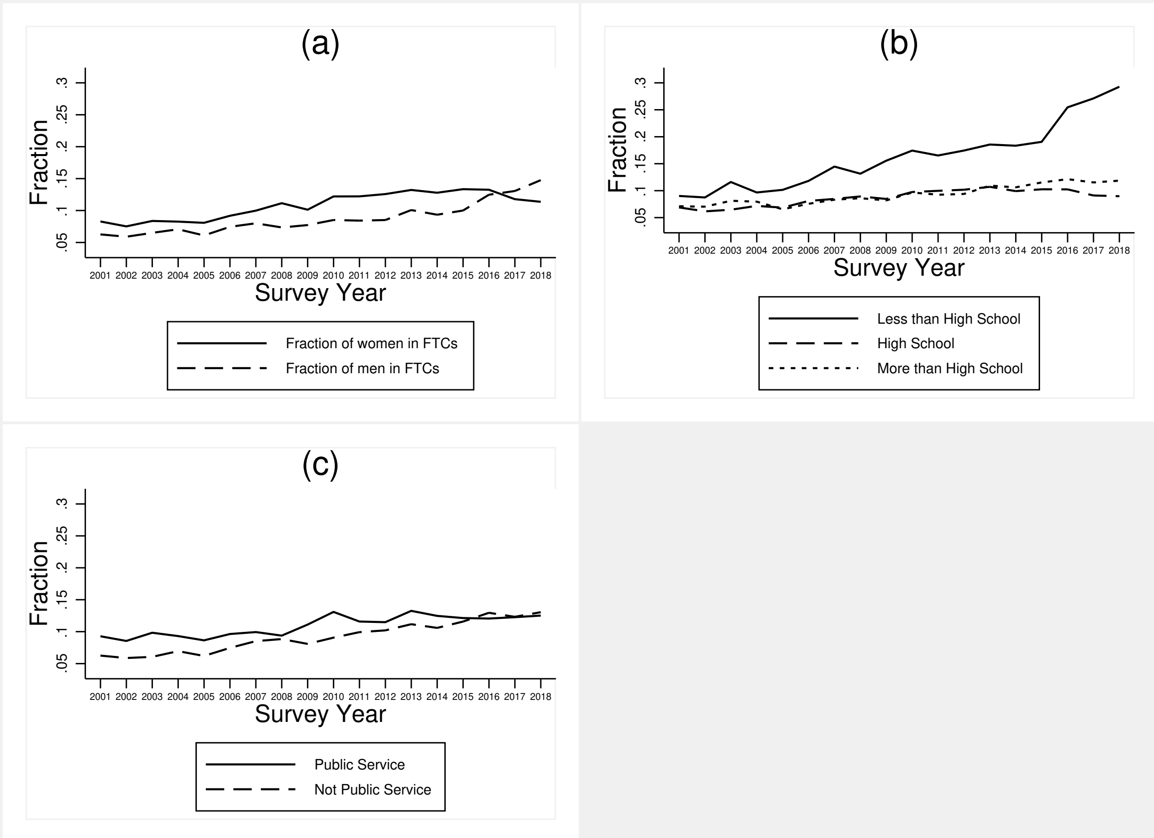
[20] Data partitions are used to test for overfitting.

containing tax, pension, or transfer information). The final dataset comprises 78 continuous, 54 categorical (or factor), and 20 dummy variables. All variables are standardised by default.

The following descriptives concentrate on control variables usually used in the literature. The fraction of FTC workers has increased since 2001 and the increase differs by subgroup. Figure 2.1 shows the evolution of the fraction of FTC workers (compared to PC workers) over the considered period by gender (panel a), education with respect to high school (panel b), and being employed in public service (panel c). The fraction of female FTC workers is higher over the whole considered period until 2016, indicating a gender-relation of the FTC probability (panel a). The steep increase in male FTC workers after 2016 purely comes from non-German nationals. This holds for the increase in the lower educational group and those who are employed in the private sector in the following two panels as well.[21] Turning to the educational attainment (panel b), the fraction of lower educated FTC workers is higher than for the medium and higher educational groups. This goes in line with findings from the literature. Considering employment by sector (panel c), the fraction of public service FTC workers is higher than for the private service, which reflects findings from the literature as well.
Descriptives for continuous variables and categorical variables with many categories are displayed in table 2.2. Regarding the age, the mean supports the result from the literature that the FTC probability declines with age, as it is approximately 6 years lower for FTC than for PC workers on average. The marital status and the number of children seem to matter less. The full-time working experience is about seven years lower and the unemployment experience one year higher for FTC workers, which also reflects results from the related literature. Turning to occupations, differences in fractions of FTC and PC workers are not remarkable. This could be related to the fact, that only occupations at a 1-digit level are displayed, which do not account for positional differences within occupations.

[21] Results that show the dependency on the nationality can be obtained by the author upon request. In the following analyses all nationalities available in the SOEP are considered.

Figure 2.1: Fraction of FTC Workers by Subgroup



Data Source: soep.v35, 2019.

Table 2.2: Descriptives by Contract Type

	FTC			PC		
	Mean	SD	N	Mean	SD	N
Age	37.67	11.01	20180	43.95	10.15	180646
Marital Status:						
Married	.5	.5	20060	.66	.47	179669
Single	.03	.17	20060	.03	.16	179669
Widowed	.37	.48	20060	.2	.4	179669
Divorced	.09	.29	20060	.1	.29	179669
Separated	.01	.1	20060	.01	.12	179669
Number of Children	.9	1.12	20180	.84	1.06	180646
Full-Time Experience	9.44	9.78	19874	16.67	11.25	178410
Part-Time Experience	2.82	4.63	19874	3.38	5.93	178410
Unemployment Experience	1.54	2.99	19874	.57	1.63	178410
Occupation, 1-Digit:						
Managers	.03	.17	17579	.06	.23	173577
Professionals	.2	.4	17579	.18	.39	173577
Technicians and Associate Professionals	.2	.4	17579	.25	.43	173577
Clerical Support Workers	.1	.29	17579	.12	.32	173577
Services and Sales Workers	.16	.37	17579	.11	.31	173577
Skilled Agricultural, Forestry and Fishery Workers	.01	.11	17579	.01	.09	173577
Craft and Related Trades Workers	.1	.3	17579	.13	.34	173577
Plant and Machine Operators and Assemblers	.07	.26	17579	.08	.26	173577
Elementary Occupations	.13	.33	17579	.07	.26	173577

Notes: Descriptives are based on the final dataset used and refer to covariates used in *Benchmark I*. The mean, the standard deviation, and the number of observations are displayed separately for FTCs and PCs. Data Source: soep.v35, 2019.

2.4 Methodology

The main goal of this chapter is to find a model that predicts the belonging to the class of FTC workers with a high level of accuracy and to analyse included determinants (referred to as "prediction task"). The second goal is to compare results regarding the coefficients of included variables from the shrinkage methods to results from the literature. Therefore, I perform an "inference task".[22] To be clear about this aspect, it is important to understand that machine learning methods are not intended to make statements about inference.
Mullainathan and Spiess (2017), pp. 87-88 get to the heart of it:

> *"Central to our understanding is that machine learning not only provides new tools, it solves a different problem. Machine learning (or rather "supervised" machine learning, the focus of this article) revolves around the problem of prediction: produce predictions of y from x. [...] It manages to fit complex and very flexible functional forms to the data without simply overfitting; it finds functions that work well out-of-sample."*

Following this argument, the purpose of the prediction task applying LASSO and Elastic Net is solely to find a model that selects relevant controls for predicting the class belonging. As I describe in the presentation of the methods used below, one cannot directly interpret coefficients of these controls from LASSO and Elastic Net and, accordingly, cannot compare them to coefficients from the literature. To circumvent this problem and to draw inferential conclusions, I apply the Double Selection LASSO of Belloni et al. (2014b).

First, I use four benchmark models including common variables from literature or all available variables. Second, I compare predictive accuracy results to models I find applying LASSO and Elastic Net. Third, I turn to the inference task. As first benchmark (hereinafter *Benchmark I*, BI), I perform a logistic regression including variables that are usually used in the related literature and asses the predictive performance of this model. The analysis of Hagen (2002) provides a richer set of control variables compared to other analyses and includes several interactions. Therefore, my second benchmark model (hereinafter *Benchmark II*, BII) is closely related to his analysis to test the accuracy of a model with a larger number of controls selected on domain

[22] Referred to as statistical inference. Causality is beyond the scope of this analysis.

knowledge.[23] Following the considerations on the related literature in section 2.2.2, the following variables are included in the logistic regression building the *Benchmark I* model: The age and its squared, the gender, the marital status, the number of children, the educational level, the occupation, the working and unemployment experience, and being employed in the public sector.

For the *Benchmark II* model, I use a richer set of controls. Following considerations of Hagen (2002), I include the following variables and interactions: the gender, the school degree, the unemployment experience, the working experience (full-time and part-time) as provided in the SOEP, a variable that includes a self-calculated experience[24], an indicator of working in the public service and its interaction with the calculated experience, and an interaction term between the self-calculated experience and the female indicator. Additionally, I include dummy variables that indicate whether individuals began a new employment in the respective last year, whether they were not employed or unemployed in the respective last year, whether they were dismissed by the former employer, whether they are married or divorced, whether their spouse is employed interacted with the female indicator, and whether their spouse was dismissed by his/her former employer. I also include the number of children in the household and its interaction term with the married indicator. The indicator for being married and being divorced are interacted with the female dummy as well. The occupation and the firm size are included additionally.

As a third benchmark model (hereinafter *Benchmark III*, BIII), I include variables from *Benchmark I* plus all other control variables available in the dataset to satisfy the objection whether the model would not perform even better if one simply used all available variables. I show that the prediction accuracy then suffers from overfitting. As a fourth benchmark model (hereinafter *Benchmark IV*, BIV), I include all variables from *Benchmark III* plus additional manually selected interaction terms.[25] In all four benchmark models, standard errors are clustered at the

[23] Hagen (2002) uses data from the SOEP but only for the year 1999. I have to make the following three adaptations: first, he uses a variable that indicates the importance of work to individuals. As this variable is not available for all years in my sample, I exclude it. Second, he uses a different definition of the educational attainment. I include the school degree to capture education related heterogeneity. Third, as it is not completely comprehensible how he formed occupational groups, I include occupations at a 1-digit level. The resulting occupational groups are are quite similar to those he uses.

[24] Following Hagen (2002) this variable is calculated as age minus school years minus six.

[25] The following interaction terms are included: age $\times$ full-time experience, age $\times$ part-time experience, female $\times$ occupation, female $\times$ industry, female $\times$ occupational position, female $\times$ full-time experience, female $\times$ part-time experience, female $\times$ unemployment experience, ISEI-score $\times$ occupation, and ISEI-score $\times$ industry. Interactions where chosen manually by applying domain knowledge and assessing the improvement of the model fit.

individual level and the survey years are included to account for the panel character of the dataset. The coefficients of the four benchmark models are less relevant than their predictive accuracy for the prediction task.

In a next step, I run a LASSO regression and an Elastic Net regression to select models based on these methods using the training dataset. To asses the predictive performance of the methods, I predict the probability of having an FTC using the validation dataset and compare the performance using different cut-off values for the class assignment.

The LASSO regression, first introduced by Tibshirani (1996), minimises the objective function including a penalty term for coefficients: the penalty term consists of the tuning parameter and the sum of the absolute values of the coefficients. With this procedure, some coefficients are set to zero and such the corresponding explanatory variables are excluded from the regression. Following, the LASSO regression performs a variable selection in contrast to e.g. the Ridge regression.[26] The optimisation problem using Stata's `lasso logit` command is denoted by the following equation (StataCorp. (2021), pp.158ff). Equivalently to the linear LASSO regression procedure, the logistic LASSO regression minimises the negative log likelihood function but with adding a penalty term:

$$\min_{\beta} \frac{1}{N} \sum_{i=1}^{N} w_i \Big(-ftc_i(\beta_0 + x_i\beta') + ln\{1 + exp(\beta_0 + x_i\beta')\} \Big) + \lambda \sum_{j=1}^{p} \kappa_j |\beta_j| \tag{2.1}$$

with w_i as observation-level weights, ftc_i as binary variable for being employed on a fixed-term basis (outcome variable), β_0 as constant, β as vector of coefficients corresponding to x_i as vector of control variables, and λ as the tuning parameter. The second sumand denotes the penalty term. It is defined by the tuning parameter λ and the sum of absolute values of βs. The design of the penalty parameter is such that by taking partial derivatives w.r.t. β, the βs can become zero if λ is sufficiently large. The optimal λ is chosen by 10-fold cross validation in my analysis (for both LASSO and Elastic Net). κ_j are the coefficient level weights which are

[26] Tibshirani (1996) interprets this as a drawback of the Ridge regression as a large number of variables goes to the expense of the interpretability of the model. Still he finds that Ridge regression can outperform LASSO regression if there are many explanatory variables with only small effects on the dependent variable (see Tibshirani (1996), pp. 282ff). To ensure the interpretability of the chosen models, I concentrate on shrinkage methods that perform a variable selection.

set to 1 by default.[27]

The Elastic Net regression, first introduced by Zou and Hastie (2005), combines the Ridge and LASSO regressions by adding two penalty terms, a squared and an absolute-value penalty term, weighted by an additional penalty parameter α. I perform regressions using Stata's `elasticnet logit` command, where the optimisation problem is presented equivalently as follows (StataCorp. (2021), pp.158ff):

$$\min_{\beta} \frac{1}{N}\sum_{i=1}^{N} w_i\Big(-ftc_i(\beta_0+x_i\beta')+ln\{1+exp(\beta_0+x_i\beta')\}\Big)+\lambda\sum_{j=1}^{p}\kappa_j\left\{\frac{1-\alpha}{2}\beta_j^2+\alpha|\beta_j|\right\} \tag{2.2}$$

Only the penalty term changes compared to equation 2.1: it is now the combination of the Ridge (squared term) and the LASSO penalty. α is an additional penalty parameter, with $\alpha \in [0;1]$. $\alpha = 1$ yields the LASSO regression, $\alpha = 0$ the Ridge regression. A solution procedure proposed by Zou and Hastie (2005) is to select a finite number of αs on which the λ optimisation is performed. The optimal combination of α^* and λ^* is, as stated by Zou and Hastie (2005), the one that minimises the Cross Validation error. As the goal of this chapter is to identify relevant control variables and such to perform a variable selection, I restrict the values of α to $\alpha \in [0.5;1]$. With this procedure, the resulting model will be closer to the LASSO than to the Ridge solution. In the analysis below, tested αs range from 0.5 to 1 in steps of 0.05 and the applied algorithm chooses an optimal $\alpha^* = 0.8$.

Considering the problem at hand, the analysis of the determinants of the FTC probability, it is not clear in advance which of the selection models will perform best. According to Zou and Hastie (2005), one advantage of the Elastic Net regression over the LASSO regression is that Elastic Net includes groups of variables with high correlations whereas LASSO tends to use only one variable of these groups and exclude the rest, i.e. Elastic Net rather shrinks the group of correlated parameters and use them all for regression or removes all of them. I apply both models and compare their predictive performance.

For the performance evaluation of the models, I use the deviance and the deviance ratio. The deviance ratio is calculated as $D^2 = \frac{D_{cons}-D}{D_{cons}}$, i.e. the fraction of the difference of the deviance of the model where only the constant term is included (D_{cons}) and the full model‘s deviance (D)

[27]This aspect is further considered below in the part regarding the adaptive LASSO.

divided by the constant term deviance.[28]

In a next step, I compare the sensitivity of the two models to the sensitivity of the benchmark models. Following the standard definition, the sensitivity is calculated as the number of correctly classified FTC workers (true positives, denoted by *TP*) divided by the number of real FTC workers, consisting of correctly classified FTC workers plus incorrectly classified FTC workers (false negatives, denoted by *FN*): Sensitivity = $\frac{TP}{TP+FN}$.

As a first robustness test, I choose a different way for splitting the sample. In the main regressions, I split the sample randomly by using Statas's `splitsample` command, as it is recommended by the Stata manual. A random split is usually used in literature (see e.g. Mullainathan and Spiess (2017)). To assess the robustness of this procedure, I use a 10-fold cross validation (hereinafter denoted by CV) to split the sample in the following way: I generate one random number for each individual used to split the sample into ten groups of equal size. Then each of those ten groups is used subsequently as the validation dataset, whereby the other groups form the training set, respectively. As this procedure is exceptionally computationally intensive I apply it only for the evaluation of the pure LASSO results and not for Elastic Net.[29]

As second robustness test, I apply an adaptive LASSO model which uses a different method for selecting the optimal tuning parameter λ^*. What one has to keep in mind with data driven methods is that the results depend on the underlying data structure that can lead to the choice of different models. As Zou (2006) shows, the original LASSO fails to be consistent if irrelevant variables are included, and introduces a method to circumvent this problem. His adaptive LASSO adds coefficient level weights that may be unequal to one in equation 2.1. These coefficient level weights are defined as $\kappa_j = \frac{1}{|\hat{\beta}|_j}$ (Zou (2006), p. 1424). The algorithm works in two steps: first, LASSO regression selects certain controls and calculates corresponding coefficients. Second, another LASSO regression performs a second variable selection testing only the selected coefficients from the first step. Both steps apply cross validation (CV). The adaptive LASSO uses a different tuning than the original LASSO and usually includes less control variables. Thereby, it excludes irrelevant variables only capturing noise that the original LASSO

[28]See StataCorp. 2019. Stata 16 Base Reference Manual. College Station, TX: Stata Press. `lassogof` Methods and Formulas Manual, p. 226.

[29]It takes about 61 hours to run a simple Elastic Net regression for only one fold, so it would take about 25 days to run regressions on a 10-fold split. As results will show in the next section, models resulting from LASSO and Elastic Net are quite close, so that I consider it as sufficient to test only the LASSO.

kept in the first place.

One goal of this chapter is to find a model that best predicts the belonging to the class of FTC workers by applying machine learning methods that select control variables automatically without too much of a manual pre-selection. The goal is achieved with LASSO and Elastic Net applications, as described in the previous paragraphs. Besides increasing the predictive power of the model in the prediction task, a second goal of this paper is to make some statements about the included controls (referred to as "inference task").[30] Thereby one has to consider the following limitations: first, we cannot compare coefficients from the logistic regression to coefficients from the LASSO logistic regression because (as equation 2.1 shows) we are optimising a different objective function compared to a pure Logistic regression leading to differing coefficients. As becomes evident from the optimisation problem shown in equation 2.1 and considerations by Tibshirani (1996), equations (5) and (6), p. 272, the Lasso estimate cannot equal the non-shrinkage estimate as the Lasso technique introduces a bias to the estimate. It is precisely the goal of LASSO to perform variable selection by shrinking some coefficients to zero. According to Belloni et al. (2014b), this can lead to the result that very small coefficients are set to zero, even if the control would belong to the true model.

Second, with a pure LASSO, one might face problems in estimating standard errors. The introduction of the penalty term, which is also subject to uncertainty, leads to a non-trivial problem: the coefficients vary with the choice of the penalty parameter, which introduced additional uncertainty, and the underlying distribution of the estimator is not clear (see e.g. Tibshirani (1996), Leeb and Pötscher (2008), Berk et al. (2013), and Mullainathan and Spiess (2017)). Tibshirani (1996) proposes to use a bootstrap procedure to circumvent this issue but several authors show, bootstrapping might lead to inconsistent estimates (see e.g. Fu and Knight (2000), Chatterjee and Lahiri (2010) or Casella et al. (2010), who show that bootstrapping fails to estimate correct standard errors, if coefficients are zero). The aspect of the underlying distribution has been considered by various authors. Leeb and Pötscher (2008) show that under certain conditions it is not possible to estimate the underlying distribution. Following, the variance and resulting standard errors cannot be estimated. A number of authors addressed this problem by different ways of estimating the underlying variance.[31] As coefficients estimated by the two shrinkage

[30] See Mullainathan and Spiess (2017) and Angrist and Frandsen (2022) for a discussion of this distinction.

[31] See Reid et al. (2016) for a review of some variance estimators proposed in the related literature and a simulation study about their performance.

methods used are biased per se, their standard errors are not of interest in the analysis at hand, this aspect is beyond the scope of this chapter and is not further considered here.

To deal with the above stated shortcomings of the shrinkage methods, I apply a LASSO for inference model, namely a double selection model. Belloni et al. (2014b) state that applying a LASSO for variable selection and including these selected controls in a second regression to draw inferential conclusions can lead to incorrect results. The problem is that with data driven methods that depend on the underlying data structure, there is no one hundred percent certainty that the correct variables have been selected: especially if coefficients are very small it might very well be that LASSO omits them which would lead to the endogeneity problem of omitted variable bias (OVB). The problem is especially pronounced, according to Belloni et al. (2014a), if there is high correlation between the control variables. To circumvent this problem, Belloni et al. (2014a) use a double selection model that works in subsequent steps as presented below. I perform regressions using Stata's `dslogit` command, where the regression equation is presented following Belloni et al. (2016) as (StataCorp. (2021), p. 52):

$$E[ftc|d,x] = \frac{exp(d\gamma' + \beta_0 + x\beta')}{1 + exp(d\gamma' + \beta_0 + x\beta')} \tag{2.3}$$

with d being the vector of control variables of interest, in this case *Benchmark I* controls, γ as the vector of corresponding coefficients, x as the vector of additional controls, and β the vector of corresponding coefficients. The intuition proposed by Belloni et al. (2014a) and Belloni et al. (2014b) is to use LASSO for the outcome (here ftc) on the additional controls x, then to use a LASSO for the control variables of interest d on the additional controls x, and then apply a LASSO for regressing the outcome ftc on d and the additional control variables that have been selected in both prior steps uniformly (see Belloni et al. (2014a), p. 37, and for a more technical explanation StataCorp. (2021), p. 52). I cluster standard errors at the individual level to ensure comparability to *Benchmark I* results.

Applying the double selection method, I aim at finding a model in which the OVB is as low as possible (compared to the simpler benchmark models). Belloni et al. (2014b) show that under certain conditions the double selection methods they propose are designed to control for omitted variable bias.[32] Furthermore, Belloni et al. (2014b) state that applying a double selection method results in consistent standard errors.

Nevertheless, I make no claim that my resulting models produce causal results. The aspect is taken up in Angrist and Frandsen (2022), who propose that Machine Learning methods can support "classical" identification strategies by helping to choose control variables. In their analysis using post-double-selection LASSO, they find that it depends on the method of choosing the tuning parameter, which control variables are selected but also that coefficients of interest do not vary considerably between different specifications. Still, Wüthrich and Zhu (2020) show that there are cases where relevant control variables are omitted by both steps of the double-selection procedure, which suggests that OVB cannot always be excluded with this procedure. Angrist and Frandsen (2022) emphasise that even if it can be possible to find a causal effect with post-double-selection as proposed by Belloni et al. (2014b), causality still depends on the conditional independence assumption and cannot be used per se as an identification strategy. Using the resulting model from this chapter as a basis for identification strategies is beyond the scope of this analysis. As the analysis of this chapter is supposed to stay descriptive, this aspect is not further considered here and stays for further research.

2.5 Results and Robustness

2.5.1 Results

Results regarding the coefficients of the benchmark models are not relevant for the prediction task but rather for the inference task presented below. Nonetheless, I show estimated coefficients for completeness: Results from the first two benchmark models are mainly in line with findings from the literature (2.3). Considering the simpler model *Benchmark I*, an increasing age is associated with a significantly lower FTC probability, as are higher levels of education and longer working experience. Public sector employees are associated with a higher FTC probability than employees in the private sector. Contrary to the findings from literature, the marital status (being separated, being single, and being divorced), and being female are significantly associated with the FTC probability. The results from the *Benchmark II* regression are also mainly in line with the findings from literature: Negative signals, such as the unemployment experience, not working in the previous year, having been dismissed by the former employer,

[32] A further discussion on this point can be found in Belloni et al. (2014b) and is beyond the scope of this analysis.

and a new employment since the last year are associated with an increased FTC probability, whereas positive signals like a longer working experience or a higher school degree show a negative correlation. The result that public service employment affects FTC probability significantly positive supports the findings in previous literature as well. Coefficients of variables related to the spouse of individuals seem to have no significant effect, nor has the number of children, the marital status, or the firm size. The occupation seems to matter in that *Professionals* and *Skilled Agricultural, Forestry and Fishery Workers* are associated with a significantly higher FTC probability than *Plant and Machine Operators and Assemblers*. In contrast to the analysis of Hagen (2002), the coefficient of the female indicator is highly significant in my analysis indicating a certain gender-relation of the contract type.

Turning to *Benchmarks III* and *IV*, the age coefficient looses its significance. In *Benchmark IV* the interaction effects between age and experience measures are small but highly significant. The female coefficient becomes insignificant in *Benchmark III* and is negative and significant in *Benchmark IV*, where the variable is interacted with the occupation, the industry, the occupational position, and the experience.[33] Coefficients of the interaction terms indicate a certain interdependency of these variables. The coefficients of education with respect to high school loose their significance and results for the different occupation differ compared to *Benchmarks I* and *II*.

[33]Due to these interactions, the female coefficient in *Benchmark IV* cannot be interpreted separately has to be considered in relation to interacted variables. The interaction terms were inserted to improve the accuracy of the predictions.

Table 2.3: Determinants of FTCs - Benchmark Models

Variable	Benchmark I	Benchmark II	Benchmark III	Benchmark IV
Dependent variable: Binary for working in FTC/PC				
Age	-0.126***		-0.320	-0.409
	(0.015)		(0.254)	(0.269)
Age squared	0.002***			
	(0.000)			
Female	0.128***	0.682***	0.084	-2.409**
	(0.045)	(0.220)	(0.104)	(1.218)
Married		-0.272**		
		(0.106)		
Divorced		-0.121		
		(0.167)		
Marital Status:				
Married, but separarted	0.183**		-0.091	-0.132
	(0.089)		(0.196)	(0.206)
Single	0.149***		0.370***	0.339**
	(0.050)		(0.131)	(0.134)
Divorced	0.204***		0.266*	0.286*
	(0.062)		(0.157)	(0.156)
Widowed	-0.092		0.070	0.035
	(0.174)		(0.331)	(0.333)
Female × Experience clac.		-0.014**		
		(0.007)		
Female × Married		-0.136		
		(0.125)		
Female × Spouse Non-Employed		-0.296		
		(0.181)		
Married × Number of Children		-0.060		
		(0.058)		
Female × Divorced		0.058		
		(0.195)		
Spouse Dismissed		0.172		
		(0.192)		
Number of Children	0.029	-0.020	0.005	0.014
	(0.018)	(0.044)	(0.143)	(0.147)
School Degree:				
Secondary School Degree		-0.382**		
		(0.187)		
Intermediate School Degree		-0.479**		
		(0.186)		
Technical School Degree		-0.573***		
		(0.213)		
Upper Secondary Degree		-0.432**		
		(0.201)		
Other Degree		0.056		
		(0.197)		
Educ. wrt. High School:				
High School	-0.321***		0.030	0.071
	(0.054)		(0.385)	(0.376)
More than High School	-0.287***		-0.934	-0.779
	(0.073)		(0.943)	(0.880)
Experience calc.		0.025***		
		(0.008)		
Unemployment Experience	0.153***	0.137***	0.056***	0.100***
	(0.009)	(0.012)	(0.016)	(0.022)
Part-Time Working Experience	-0.074***	-0.040***	-0.020*	-0.082*
	(0.006)	(0.008)	(0.011)	(0.048)
Full-Time Working Experience	-0.068***	-0.053***	0.001	-0.107***
	(0.004)	(0.006)	(0.009)	(0.028)
Occupation 1-Digit:				
Managers	-0.475***	-0.265	-0.121	1.420
	(0.130)	(0.193)	(0.451)	(2.351)
Professionals	0.038	0.296**	0.467	0.244
	(0.084)	(0.132)	(0.410)	(1.442)
Technicians and Associate Professionals	-0.277***	-0.062	0.256	1.832
	(0.070)	(0.110)	(0.332)	(1.344)
Clerical Support Workers	-0.254***	-0.163	0.389	2.505*
	(0.077)	(0.122)	(0.304)	(1.340)
Services and Sales Workers	0.095	0.105	0.317	1.781
	(0.072)	(0.116)	(0.255)	(1.339)
Skilled Agricultural, Forestry and Fishery Workers	0.516***	0.858***	1.072***	-33.578*
	(0.173)	(0.234)	(0.395)	(19.876)
Craft and Related Trades Workers	-0.236***	-0.049	0.448**	2.836**
	(0.073)	(0.117)	(0.189)	(1.367)
Elementary Occupations	0.204***	0.155	0.322	1.285
	(0.075)	(0.123)	(0.206)	(1.427)
Public Service Employee	0.311***	1.174***	0.793***	0.745***
	(0.042)	(0.153)	(0.110)	(0.111)
Public Service Employee × Experience calc.		-0.029***		
		(0.006)		
New Work since last Year		2.016***		
		(0.051)		
Not Employed or Unemployed last Year		0.318***		
		(0.103)		
Dismissed by fomrer Employer		0.544***		
		(0.122)		
Firm with more than 200 Employees		0.059		
		(0.054)		
Constant	-54.186***	-34.682***	159.584	197.873
	(6.558)	(9.848)	(123.936)	(132.046)
Survey Year	0.028***	0.016***	0.144	0.201
	(0.003)	(0.005)	(0.263)	(0.276)
Additional Variables	No	No	Yes	Yes
Pseudo R-Square	0.103	0.209	0.381	0.402
Number of Obs.	108,418	62,943	38,327	38,305

Note: Regressions are estimated with Logit. The first column *Benchmark I* gives regression results for the model including usual control variables from literature. The base category for the Marital Status is *Married*, for the Education with respect to High School it is *Less than High School*, and for the Occupation it is *Plant and Machine Operators and Assemblers*. The column *Benchmark II* gives regression results including the controls based on Hagen (2002). The base category for the School Degree is *No Degree* and for the Occupation *Plant and Machine Operators and Assemblers*. Experience calc. is calculated as age minus years in school minus 6. The column *Benchmark III* gives regression results for the model including *Benchmark I*-variables plus all additional variables available. The column *Benchmark IV* gives regression results for the model including all variables from *Benchmark III* plus the following interaction terms: age × full-time experience, age × part-time experience, female × occupation, female × industry, female × occupational position, female × full-time experience, female × part-time experience, female × unemployment experience, ISEI-score × occupation, and ISEI-score × industry. Standard errors are in parentheses and are clustered at the individual level. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Data Source: soep.v35, 2019.

Turning to results from the prediction task, the first part of table 2.4 shows sensitivities for the four benchmark models. The predictive performance of the first two benchmark models is rather poor with the more complex model performing somewhat better than the simpler one in predicting the belonging to the class of FTC workers.[34] *Benchmark I* yields a sensitivity of the of 2.6% for a cut-off of 0.5 and of 14.4% for a cut-off of 0.25, respectively and the *Benchmark II* model provides a sensitivity of 11.5% (29.1%, respectively). Although including all available variables comes with the risk of overfitting, *Benchmarks III* and *IV* perform better in predicting the belonging to the class of FTC workers. Their sensitivities do not differ considerably with around 28% (50%, respectively).

Lasso and Elastic Net perform better in predicting the belonging to the group of fixed-term workers compared to the simpler benchmark models. The lower panel of table 2.4 shows the corresponding sensitivities.[35] The sensitivity of the LASSO model and a cut-off of 0.5 (0.25) is 31.9% (59.2%) and for the Elastic Net model it is slightly lower at 31.7% (58.7%).

Table 2.4: Sensitivities of BI, BII, BIII, BIV, LASSO, and Elastic Net

Specification	Senstitivty, 0.5	Sensitivity, 0.25
BI	2.64	14.41
BII	11.47	29.09
BIII	27.12	49.48
BIV	28.83	50.52
Lasso	31.88	59.14
Elastic Net	31.65	58.72

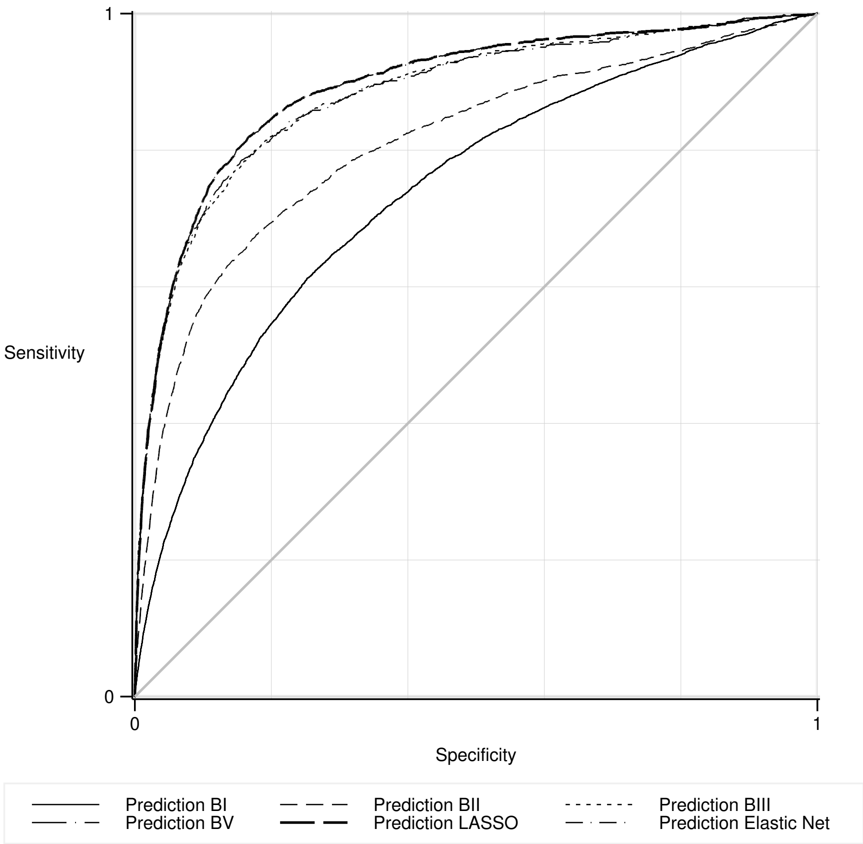
Note: The coulums present the sensitivity for cut-off values of 0.5 and 0.25, respectively. The senisitivity is calculated as described in section 2.4. Data Source: soep.v35, 2019.

Table 2.4 shows sensitivities only for two selected cut-off values. To demonstrate the superiority of the shrinkage models for other cut-off values, figure 2.2 shows the Receiver Operating Characteristic (ROC) Curves for the four benchmark models, the LASSO, and the Elastic Net model: *Benchmarks I* and *II* are clearly inferior compared to the other three models in terms of their predictive performance. *Benchmarks III* and *IV* are closer to each other and to the shrinkage models but still have a smaller area under the curve (AUC). The LASSO and Elastic Net

[34] Table A.1 shows the confusion matrices of *Benchmark I* and *Benchmark II* with cut-off values of 0.5 and 0.25 for predicting the class belonging in the validation data. Considering the cut-off value of 0.5, the *Benchmark I* model performs poorly in predicting the belonging to the class of FTC workers: only 158 individuals in the validation dataset would be classified correctly as FTC workers.

[35] Tables A.2 and A.3 show the corresponding confusion matrices of the numbers of correctly and incorrectly classified workers.

Figure 2.2: ROC of the Different Models



ROC curves differ only marginally from each other and provide the largest AUC.

The LASSO and Elastic Net regressions differ compared to the benchmark models in that they include more variables than the first two benchmark models but less then the second two and they show a better out-of-sample prediction. Considering the number of included variables, LASSO and Elastic Net include categories of factor variables as dummies in the regressions. There are 377 potential variables that could be selected. Table 2.5 shows the number of potential and selected variables for the two methods. The LASSO regression includes 184 variables and the Elastic Net regression includes 191.[36] Table 2.6 shows the goodness of fit statistics for the two models. As the logistic regression uses maximum likelihood estimations, I display the deviance and the deviance ratio. For the two models, the deviance using the validation dataset is slightly higher than with using the training dataset. Following, the deviance ratio is smaller using the validation dataset. The deviances and deviance ratios do not differ markedly comparing the training and validation datasets in the two models. From this result I suggest that the

[36] For the Elastic Net regression, the algorithm chooses an optimal α of 0.8. Therefore, results from the Elastic Net regression will be closer to results from the LASSO regression than to potential results from Ridge regression, where the α would equal zero.

out-of-sample predictions are not much worse than the in-sample predictions and the models perform well. Comparing the models shows that Elastic Net is slightly superior in terms of the deviance.

Table 2.5: Variable Selection

Method	Lasso	Elastic Net
Num of Observations	38535	38535
Num of Potential Variables	377	377
Num Nonzero Coeffs Selected	184	191
Value of Selected Lambda	.0007126	.0008584

Notes: The table displays the number of observations, the number of the potential control variables, the number of the selected control variables, and the value of the selected λ for the different methods. As selection method, I use cross validation (CV) with 10 folds. For the Elastic Net regression, the algorithm selects an optimal $\alpha = 0.8$. Logit regressions were applied. Data Source: soep.v35, 2019.

Table 2.6: Comparison of Classification Performance

	Deviance	Deviance Ratio	Obs
LASSO Training	.3176729	.3811628	47151
LASSO Validation	.3346913	.3306714	30857
Elastic Net Training	.3174856	.3815277	47151
Elastic Net Validation	.3345648	.3309243	30857

Notes: The table displays deviance, the deviance ratio, and the number of observations for the different methods for the training and the validation datasets. As selection method, I use cross validation (CV) with 10 folds. For the Elastic Net regression, the algorithm selects an optimal $\alpha = 0.8$. Logit regressions were applied. Data Source: soep.v35, 2019.

The Elastic Net model performs better in terms of the deviance and the LASSO model performs better in terms of the sensitivity. Both models outperform the benchmark models suggesting that the latter exclude variables essential for the correct classification of FTC workers or overfit the data. From this result I conclude that using a more but not too complex model and making use of the rich information in the SOEP data can increase the quality of the model.

Which variables are included by the shrinkage methods? The Lasso and Elastic Net models select nearly all variables that the *Benchmark I* and *Benchmark II* models include as well and add various additional variables. Table 2.7 gives an overview over the variables included in *Benchmark I*, *Benchmark II*, and selected by LASSO and Elastic Net models. For the sake of conciseness, variables are partially grouped in this table.[37] Compared to the *Benchmark I* model, the LASSO and the Elastic Net include all variables from *Benchmark I* except for the full-time working experience and the female indicator.[38] Comparing the selected variables to the *Benchmark II* model, LASSO and Elastic Net include all variables from *Benchmark II* except any interaction terms, which were excluded because of computational restrictions, the dismissal of the spouse indicator, the full-time working experience, and the female indicator.[39] Turning to variables that are selected by the LASSO and the Elastic Net but not included in the first two benchmark models, I group characteristics into 6 categories: personal characteristics, partner characteristics, educational characteristics, job characteristics, employment history characteristics, and other characteristics including other than labour income components. First, considering personal characteristics, LASSO and Elastic Net select, besides the above mentioned, variables containing information about the relation to the household head and for living in West Germany. Second, Variables containing information about the partner are included, as e.g. the employment level of the partner and whether the partner lives in the household. Therefore, the family/household formation seems to have an influence in this regard.[40] Third, regarding the educational attainment it has been found in literature that the educational attainment has an effect on the FTC probability. This is reflected by the selection of several variables considering educational degrees in the LASSO and the Elastic Net regressions. The school leaving degree (and the school leaving degree outside Germany) is included as is the received vocational degree (and the vocational degree received in East Germany). The type of the tertiary degree is included in both models. Comparing selection models to benchmark models, included controls for the educational attainment are more differentiated than in the benchmark models. Fourth, considering job characteristics, industries and the statistical classification of economic activities (NACE) are included, an indicator for untrained or semi-trained blue collar workers, and the occupation on a 2-digit level. This indicates that not only the occupation might have

[37]For the sake of completeness, coefficients of all selected variables for the LASSO and the Elastic Net regression are in table A.4, Appendix A. However, the coefficients should not be interpreted directly for the above stated reasons.

[38]Shrinkage methods include the age, the marital status, the occupation, the part-time working experience, and the indicator for working in public service are included as well. Shrinkage methods include information about the number of children via variables about young household members and for the educational attainment they include variables about the school degree, the vocational degree, and the type of the tertiary degree.

[39]Information about a new employment relationship is included via another variable (new work since last year), information about dismissal is included via several variables related to job changes. It would have been interesting to also see which interaction terms LASSO includes. Here, however, the algorithm would have tested all possible combinations of interactions, which would have clearly exceeded the time horizon of the analysis.

[40]*Benchmark II* accounts for partner characteristics only in terms of the dismissal of the spouse and the interaction of the spouses employment and the female indicator.

an influence on the FTC probability but also the industry and to a certain extend the occupational level.[41] Additionally to the public service indicator, a variable about the level of civil service jobs is included. Furthermore, the training requirements of the actual job, the type of the training, and whether individuals work in occupations they were trained for are included. LASSO and Elastic Net again use more detailed information on this aspect than benchmark models. The information on the tenure of individuals is represented by the variables of the year when the employment relationship started and the length of time with the firm. Regarding the working time, the models use a variable of hours per week including overtime hours.[42] This indicates that there might be a difference in the effort provided by employees in terms of their working and overtime hours in Germany, depending on whether they are employed on a permanent or fixed-term basis, as Engellandt and Riphahn (2005) find for Switzerland and Bossler and Grunau (2019) for Germany. Considering other forms of atypical employment, a variable indicating a mini-job is included as e.g. in Giesecke and Groß (2002). Both models include the employment status and the labour force status.

Fifth, turning to characteristics of the employment history of individuals, the part-time working and the unemployment experience are included as well as the employment level, the employment status in the respective last year, and whether individuals returned from maternity protection. Additionally, both models include the annual working hours in the last year. As FTCs might last longer than one year, these variables could very well capture information on the current employment. The former employment relationship seems to be of importance as well. Several variables that contain information on job changes are included as e.g. the individual has a new job since the respective last year, an indicator for no change in the employment, and reasons for occupational changes. LASSO and Elastic Net regressions do not include whether individuals were terminated by the former employer. Nevertheless, from the inclusion of other variables linked to job changes, this information is included to some extend. Variables about the employment prospects at the end of the last employment relationship and information on the search of the current job are included.

Sixth, considering other characteristic, another notable aspect is that many variables containing information about the health status, about health and life satisfaction, and about worries of

[41] Giesecke and Groß (2002) accounts also for the occupational position to a certain extent.

[42] Both variables "Actual Work Time per Week" and "Actual Working time with overtime hours/week" are based on the same survey question and measure the working time per week including overtime hours. The only difference is the source dataset: the first variable is taken from the generated dataset *pgen* and the second from the core dataset *pl*.

individuals are included. This indicates that there could be systematic differences in those measures between FTC and PC workers.[43] Nevertheless, one has to keep in mind that the selection process is based on purely descriptive considerations. Therefore, endogeneity problems like reverse causality are not considered. Interestingly, there are several variables included containing information on other than labour income components. Variables comprising information on the labour income of individuals were excluded manually as they are most probably endogenous. The selection of the "Unemployment Benefit" and "Unemployment Benefit II" is not surprising as these variables capture whether individuals were unemployed in the survey year for some time. The variable "Maternity Benefit" shows also that the individual was not working for a certain period in the respective year which could influence the FTC probability. The value of general alimonies and divorce alimonies are included as are the value of the housing benefit, the value of travel grants, and the value of capital losses. Those variables are likely to reflect the economic situation of individuals and their capability to afford their living expanses by themselves. Both methods include the severance payment but use two different but equivalent variables for this purpose.[44] This could be related to the FTC probability as there is only a severance payment if the former employment relationship ended, which is related to a new employment contract that might be on a fixed-term basis. The value of the statutory accident insurance is included only in the Elastic Net regression but is of negligible size.

Summarising, the LASSO and Elastic Net regression include variables from *Benchmark I* and *Benchmark II* plus a variety of additional controls. The variables used by the two methods are more differentiated and such contain more information than those used in the first two benchmark models. Results from the selection process indicate that there are other relevant aspects as the inclusion of variables considering satisfaction, worries, and other income sources let suggest. As the SOEP data includes an immense amount of information, this feature of the dataset should be used by including more variables to models that are supposed to predict the FTC probability.

[43] As presented in section 2.2.2, Chadi and Hetschko (2016) analyse the aspect of job satisfaction and find it to be lower for FTC workers in Germany. The aspect of worries and health satisfaction measures are not considered, which could be a direction for further research.

[44] "Severance payment amount" from the core dataset *pl* used by LASSO and "Indemnity" from the dataset on extended income information *pequiv* used by Elastic Net.

Table 2.7: Included Variables by Model

Variable	BI	BII	Lasso	Elastic Net
Constant	✓	✓	✓	✓
Survey Year	✓	✓	✓	✓
Personal Characteristics:				
Living in West Germany	-	-	✓	✓
Age	✓	-	✓	✓
Age sqrt	✓	-	-	-
Female	✓	✓	-	-
Marital Status⋆	✓	✓	✓	✓
Number of Children and HH Members 0-15⋆	✓	✓	✓	✓
Relationship to HH Head	-	-	✓	✓
Partner Characteristics:				
Employment Level of Partner	-	✓	✓	✓
Partner Lives in HH	-	-	✓	✓
Dismissal of Spouse	-	✓	-	-
Educational Characteristics:				
Education wrt High School	✓	-	-	-
School Degree	-	✓	✓	✓
School-Leaving Degree Outside GER	-	-	✓	✓
Type of Vocational Degree⋆	-	-	✓	✓
Type of Tertiary Degree	-	-	✓	✓
Competed Training after 2006	-	-	✓	✓
Job Characteristics:				
Occupation	✓	✓	✓	✓
Industry	-	-	✓	✓
Level of Industrial Sector Work	-	-	✓	✓
Public Service	✓	✓	✓	✓
Level of Civil Service	-	-	✓	✓
Required Training	-	-	✓	✓
Type of Training	-	-	✓	✓
Working in Occ Trained for	-	-	✓	✓
Firm Size⋆	-	✓	✓	✓
Actual Working Time	-	-	✓	✓
Tenure⋆	-	-	✓	✓
Marginal Employment	-	-	✓	✓
Employed by Employment Agency	-	-	✓	✓
Employment Status	-	-	✓	✓
Labour Force Status	-	-	✓	✓
New Employment Relat	-	✓	-	-
Employment History Characteristics:				
Full-Time Experience	✓	✓	-	-
Working Experience (self-calculated)	-	✓	-	-
Part-Time Experience	✓	✓	✓	✓
Unemployment Experience	✓	✓	✓	✓
Employment Level Last Year	-	-	✓	✓

To be continued

Table 2.7 (continued)

Variable	BI	BII	Lasso	Elastic Net
Employment Status Last Year	-	-	✓	✓
Maternity Protection or Parental Leave	-	-	✓	✓
Annual Working Hours prev Year	-	-	✓	✓
Out of LF prev Year	-	✓	-	-
New Work Since Last Year	-	-	✓	-
Change of Job in prev Year	-	-	✓	✓
Nature of Professional Change	-	-	✓	✓
Reasons for Occ Change	-	-	✓	✓
Occupational Change	-	-	✓	✓
Perspective at the End of Employment Relat	-	-	✓	✓
Dismissed by former Employer	-	✓	-	-
Learned from from Job Through	-	-	✓	✓
Actively Sought this Position	-	-	✓	✓
Other Characteristics:				
Current Health⋆	-	-	✓	✓
Number of Doctor Visits	-	-	✓	✓
Disability Status	-	-	✓	✓
Satisfaction with Health	-	-	✓	✓
Overall and Current Life Satisfaction	-	-	✓	✓
Staisfaction⋆	-	-	✓	✓
Worries⋆	-	-	✓	✓
Time Usage (Hours)⋆	-	-	✓	✓
Benefits⋆	-	-	✓	✓
Other Financial Sources⋆	-	-	✓	✓
Losses from Capital Investment	-	-	✓	✓
Severance Payment Amount	-	-	✓	✓
Statutory Accident Insurance	-	-	-	✓
Party Preference Intensity	-	-	✓	✓

Note: The regression BII additionally includes the following interaction terms: *Public Service* × *Experience*, *Female* × *Experience*, *Spouse employed* × *Female*, *Being Married* × *Number of Children in HH*, *Being Married* × *Female*, and *Divorced* × *Female*. ⋆ denotes that variables are grouped in the table. Groups of variables include the following: *Marital Status* includes in BII dummies for being married and being divorced. *Type of Vocational Degree* covers variables for *Type of Vocational Degree*, *No Vocationsal Degree*, and *Vocational Degree outside Germany*. *Tenure* includes two variables: one indicating the year the employment relationship started and one the length of the time with the firm. *Current Health* incorporates a variables for the self-rated health status as well. *Staisfaction* include Satisfaction with Work, with HH Income, with Dwelling, and with Amount of Leisure Time. *Worries* include Worries about Economic Development, about Finances, about Own Health, about Environment, about Peace, about Crime, about Job Security, about Immigration to Germany, and about Hostility to Foreigners. *Time Usage (Hours)* include information on Homework Hours, Hours Care, Training Hours (Employed), and Hours Repairs. *Benefits* include Unemployment Benefit, Unemployment Benefit II, Maternity Benefit, and Housing Benefit. *Other Financial Sources* include Alimony, Community Travel Grand, Indemnity, and Divorce Alimony. For *Firm Size*, BII uses a variable indicating big firms with more then 200 employees. Data Source: soep.v35, 2019.

2.5.2 Robustness Tests

Cross Validation for Sample Split

Before I turn to the inference task, I present results for the robustness tests of the prediction task. To assess the predictive performance of the models, I split the sample into a training and a validation set using a random split of 60% to 40% of observations as described in section 2.4. To test the robustness of this procedure I apply a cross validation technique to split the sample: here I randomly group individuals in ten groups and use each of those groups for the validation data and the respectively remaining groups for the training data. Following, I apply the LASSO ten times and calculate the sensitivities. The mean sensitivity over the ten LASSO models (Mean CV-LASSO) is displayed in table 2.8 for Cut-Off values of 0.5 and 0.25, respectively.

Table 2.8: Sensitivities from CV Sample Split LASSO

Model	Cut-Off 0.5	Cut-Off 0.25
BIV	28.83	50.52
Original LASSO	31.90	59.14
Mean CV-LASSO	29.43	56.85
Median CV-LASSO	29.65	56.90

Notes: Sensitivities of the different models as described in section 2.4. BIV denotes the *Benchmark IV* model, CV-LASSO denotes the LASSO model for which I split the sample using cross-validation. Mean (Median) refers to the mean (median) of sensitivities of the 10-folds. Data Source: soep.v35.

The mean sensitivity of the CV-LASSO models is with 29.43% (56.85%) slightly lower than the sensitivity of the original LASSO but it is still higher than the sensitivity of the *Benchmark IV* model. This results let suggest, that applying a LASSO technique outperforms a manual variable selection if the goal is a high predictive accuracy although results from the original LASSO slightly overestimate the effect.

Adaptive Lasso

The LASSO technique is not free from potential errors and variable selection might be not accurate which is why I apply an adaptive LASSO. Table 2.9 displays the number of selected variables by the LASSO and the adaptive LASSO: the adaptive LASSO selects 48 fewer controls than the original LASSO. Again, one has to keep in mind that LASSO includes categories of factor variables as dummy variables, i.e. the lower number of controls used by the adaptive LASSO is partially due to left-out categories. An overview over the variables included by the original LASSO and the adaptive LASSO is in table A.5, Appendix A.[45] Generally, the adaptive LASSO includes fewer categories of the variables related to satisfaction, fewer occupations, and fewer industries. Adaptive LASSO does not include variables about the time usage (homework, repairs), the Mini-Job indicator, the employment level and employment status in the previous year, the reason for job changes, the school-drop out indicator, the maternity and the housing benefit, and the amount of indemnity. It includes the severance payment amount.

The adaptive LASSO is quite close to the original LASSO, which is reflected by the deviance and the deviance ratio (table 2.10). The pure LASSO seems to perform slightly better in the in-sample prediction and slightly worse in the out-of-sample prediction on basis of the deviance. Considering the sensitivity (table 2.11), the adaptive LASSO performs with 33.07% slightly better than the original LASSO with 31.9% using a cut-off value of 0.5. Lowering the cut-off to 0.25, the original LASSO performs slightly better. The comparison with the adaptive LASSO shows, that it does not perform considerably better than the original LASSO suggesting that the model chosen by the original LASSO is valid and regressions analysing the FTC probability should make use of more explanatory variables than usually used in literature.

[45] In this table only differing variables are displayed for the sake of simplicity.

Table 2.9: Comparison of LASSO and Adaptive LASSO

Method	LASSO	Adaptive LASSO
Num of Observations	38535	38535
Num of Potential Variables	377	377
Num Nonzero Coeffs Selected	184	136
Value of Selected Lambda	.0007126	.0021306

Notes: The table displays the number of observations, the number of the potential control variables, the numer of the selected control variables, and the value of the selected λ for the differend methods. As selection method, cross validation (CV) with 10 folds and adaptive was used. Logit regressions were applied. Data Source: soep.v35, 2019.

Table 2.10: Comparison of Classification Performance - LASSO and Adaptive LASSO

	Deviance	Deviance Ratio	Obs
LASSO Training	.3175541	.3813943	47151
LASSO Validation	.3431694	.3137165	30857
Adaptive Training	.3194147	.3781478	47560
Adaptive Validation	.3424208	.3150959	31156

Notes: The table displays deviance, the deviance ratio, and the number of observations for the differend methods for the training and the validation datasets. As selection method, cross validation (CV) with 10 folds and adaptive were used. Logit regressions were applied. Data Source: soep.v35, 2019.

Table 2.11: Sensitivity of LASSO and Adaptive LASSO

Specification	Sensitivity, 0.5	Sensitivity, 0.25
LASSO	31.88	59.14
Adaptive LASSO	33.08	58.87

Note: The coulums present the sensitivity for cut-off values of 0.5 and 0.25, respectively. The senisitivity is calculated as described in section 2.4. Data Source: soep.v35, 2019.

2.6 LASSO for Inference

Turning to the second goal of this chapter and thus to the inference task, I force the variables usually used in literature (*Benchmark I*) to the model and use a double-selection LASSO logistic regression to analyse changes in coefficients caused by including a broader set of additional controls selected by the LASSO. Results from the double selection model show that the directions of effects go mainly in line with findings from the literature but that the coefficients of the benchmark models seem to be biased. I use a 10-fold cross validation to choose the optimal penalty parameter λ as in the "pure" LASSO and cluster standard errors at the individual level as in the "pure" logistic regression. Table 2.12 shows regression results from the *Benchmark I* and the double-selection model for a direct comparison. Comparing the estimated coefficients across the *Benchmark I* logistic regression and the double selection logistic LASSO regression, there are some differences: the coefficient of age is still negative, larger in magnitude but significant at a lower level in the double selection logistic Lasso regression, indicating a certain bias in the coefficient in the *Benchmark I* model. The negative effect of the age on the FTC probability seems to be confirmed. The female indicator turns insignificant which corresponds to findings from literature. Results for being divorced are comparable between the models, being single has a larger effect in the double selection model. High school education does not seem to have a significant effect on the FTC probability as proposed by the *Benchmark I* model, whereas the effect of a higher education seems to be underestimated using the simple logistic model as the coefficient increases markedly using the richer set of controls. In both regressions, the unemployment, the part-time, and the full-time working experience are included.[46] The double selection model shows a smaller coefficient for unemployment experience, which is still highly significant. The part-time and full-time coefficients loose significance and become smaller indicating that the working experience matters less for the FTC probability than proposed by the *Benchmark I* model. The significant effect vanishes for most occupations.[47] Summarising, the effects of the characteristics mostly meet expectations. Still, the double selection model shows that coefficients of the simple logistic regression are biased (as it can be expected). A result that is surprising and differs from results in literature is the non-significant effect of the working experience. This effect could very well capture information from other variables that are not included in the *Benchmark I* but in the double selection model. Furthermore, the effect of some occupations seems to be overstated in the simple regression. Still, the occupation captures relevant information and has to be included in regressions analysing FTCs.

[46] One has to keep in mind that those variables might very well be collinear. For the sake of completeness, all three are included.

[47] An exception are *Skilled Agricultural, Fostery, and Fishery Workers* for which the coefficient increases markedly. The effect for *Trade Workers* even changes the sign and becomes positive.

Table 2.12: Regression Results LASSO for Inference

Variable	Benchmark I	Double Selection
Dependent Variable: Binary for working in FTC/PC		
Age of Individual	-0.155***	-0.540*
	(0.013)	(0.280)
Age squared	0.002***	0.002***
	(0.000)	(0.000)
Female	0.114***	0.070
	(0.043)	(0.103)
Marital Status:		
Married, but separarted	0.186**	-0.072
	(0.089)	(0.194)
Single	0.165***	0.349***
	(0.049)	(0.131)
Divorced	0.215***	0.258*
	(0.062)	(0.153)
Widowed	-0.099	-0.041
	(0.176)	(0.340)
Number of Children	0.028	0.031
	(0.018)	(0.141)
Educ. wrt. High School:		
High School	-0.297***	-0.267
	(0.052)	(0.375)
More than High School	-0.253***	-1.877***
	(0.070)	(0.679)
Unemployment Experience	0.153***	0.062***
	(0.009)	(0.015)
Part-Time Working Experience	-0.074***	-0.021*
	(0.006)	(0.011)
Full-Time Working Experience	-0.070***	-0.002
	(0.004)	(0.008)
Occupation 1-Digit:		
Managers	-0.475***	-0.029
	(0.125)	(0.435)
Professionals	0.047	0.512
	(0.081)	(0.398)
Technicians and Associate Professionals	-0.276***	0.295
	(0.067)	(0.327)
Clerical Support Workers	-0.258***	0.446
	(0.074)	(0.300)
Services and Sales Workers	0.063	0.368
	(0.069)	(0.255)
Skilled Agricultural, Forestry and Fishery Workers	0.436**	1.108***
	(0.171)	(0.396)
Craft and Related Trades Workers	-0.240***	0.461**
	(0.070)	(0.192)
Elementary Occupations	0.214***	0.398*
	(0.073)	(0.207)
Public Service Employee	0.348***	0.751***
	(0.040)	(0.106)
Constant	-50.596***	
	(6.171)	
Survey Year	0.026***	0.194
	(0.003)	(0.285)
Number of Obs.	111,718	40,282

Note: Regressions are estimated with Logit. The base category for the Marital Status is *Married*, for the Education with respect to High School it is *Less than High School*, and for the Occupation it is *Plant and Machine Operators and Assemblers*. Standard errors appear in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Standard errors are clustered at the individual level. The constant of the double-selection is not displayed in the vector of main coefficients but included along with the additional coefficients in the model and has a value of -57.37. Data Source: soep.v35, 2019.

2.7 Subgroup Analysis

There are some differences regarding the variables, LASSO chooses when running estimations separately for men and women. Gender is not included as explanatory variable by LASSO and Elastic Net regressions but the "pure" logistic regression shows a significant effect of the gender in *Benchmark I* and *Benchmark II* models. The effect vanishes in the Double Selection LASSO but descriptive findings indicate differences by gender. To analyse, whether determinants of fixed-term employment differ, I apply the LASSO technique by the subgroups of gender. Table 2.13 shows the deviance and the deviance ratios for the LASSO results by gender: the deviance is slightly lower for women compared to men but it is comparable to the results from the whole sample (table 2.6). The deviance ratios for men and women are slightly lower than using the whole sample, but again, they are still on an equivalent level. The out-of sample prediction is comparable to the in-sample prediction.

Table 2.13: Comparison of Classification Performance by Gender - LASSO Regression

	Deviance	Deviance Ratio	Obs
Men - LASSO Training	.3359458	.3328586	46173
Men - LASSO Validation	.3418665	.3013499	30226
Women - LASSO Training	.3176624	.3420608	55359
Women - LASSO Validation	.3337904	.3077976	36106

Notes: The table displays deviance, the deviance ratio, and the number of observations for the LASSO regressions for the training and the validation datasets by gender. As selection method, cross validation (CV) with 10 folds was used. For the Elastic Net regression, an $\alpha = 1$ was selected by the algorithm. Therefore, Elastic Net corresponds to LASSO. Logit regressions were applied. Data Source: soep.v35, 2019.

There are some differences between the variables chosen for the whole sample and the models by gender (an overview of the chosen variables with coefficients by gender is in table A.6, Appendix A). Most of the differing variables capture equivalent information and there is no information captured by the whole sample model that is not captured by the models by gender in some way.

Considering gender differences, there are some variables only included for one gender but not for the other. I concentrate on variables with the most striking economic interpretation in the following. Age is not included in the model for men suggesting that the negative association found in literature and in the *Benchmark I* model is driven by women.[48] The variable capturing information about dismissal is also only included in the model for women which indicates that the signalling function of a dismissal could be gender related. Regarding the number of children, for which there was no significant effect found in benchmark models, results from the LASSO by gender let suggest that its effect might depend on the age of the children.[49] The occupational class and the SIOPS score[50] seem only to matter for men in this regard as they are not included for women.

Gender-segregation into occupations seems to be related to the FTC probability. Some occupations are included for men but not for women.[51] Shares of men and women in these occupations are displayed in table 2.14. Most but not all of the occupations included for men are with a share of around 70% predominantly male. An exception is the occupation *Life science and health associate professionals* which only yields a share of around 15% men. The following occupations are included in the model for women but not for men: *Corporate managers*; *Other professionals*; *Models, salespersons and demonstrators*. The occupation *Models, salespersons and demonstrators* is with more than 80% predominantly female such this result is not surprising. In the occupation *Other professionals* the share of men and women is relatively balanced such it is notable that this occupation is included only in the model for women. More remarkable is the result for *Corporate managers*: here the share of women is relatively small with around 28%, still this occupation seems to be associated with the FTC probability only for women. There seems to be a gender and FTC segregation by industry. For men, seven out of 27 industries are included, for women only five. Table 2.15 shows shares of men and women in the different industries. Most industries included only for men are predominantly male with shares of male workers above 70%.[52] In *Public Administration*, shares of men and women are balanced but this industry only seems to have an effect on the FTC probability for men. In the *Wholesale* and *Service Industry*, more than half of the employees are female, still those industries are only in-

[48] The aspect of an increased FTC probability for women of childbearing age compared to men is analysed in another paper: Braschke (N.N.) *That Extra Edge - Disadvantages of Potential Mothers in Contract Duration*, chapter 2 of this thesis.

[49] The number of young household members by age is included for most age groups in the LASSO for men but only for older age groups (5-7 years, 8-10 years, and 13-15 years) in the models for women. The reason might be that a large number of women with small children is out of the labour force and therefore not considered in this analysis.

[50] Standard International Occupational Prestige Scale.

[51] *Legislators and senior officials*; *Physical and engineering science associate professionals*; *Life science and health associate professionals*; *Machine operators and assemblers*; *Labourers in mining, construction, and manufacturing*.

[52] For men, the following industries are included: *Energy, Water*; *Mining*; *Iron, Steel*; *Construction*; *Wholesale*; *Service Industry*; *Public Administration*.

Table 2.14: Fraction of Men and Women in Selected Occupations

Occupation 2-digit	Binary for being female Men %	Women %
Legislators and senior officials	70.1	29.9
Corporate managers	71.3	28.7
Other professionals	51.1	48.9
Physical and engineering science associate professionals	73.7	26.3
Life science and health associate professionals	15.6	84.4
Models, salespersons and demonstrators	17.3	82.7
Machine operators and assemblers	69.3	30.7
Labourers in mining, construction, manufacturing and transport	65.1	34.9
Total	51.6	48.4

Notes: Data Source: soep.v35, 2019. Gender shares by occupation.

Table 2.15: Fraction of Men and Women in Selected Industries

2 Digit Industry Code of Individual	Binary for being female Men %	Women %
Energy, Water	72.1	27.9
Mining	87.9	12.1
Synthetics	64.7	35.3
Iron, Steel	82.7	17.3
Electrical Engineering	73.6	26.4
Wood, Paper, Print	63.3	36.7
Clothing, Textile	37.9	62.1
Construction	86.0	14.0
Wholesale	38.6	61.4
Service Industry	40.6	59.4
Health Service	20.4	79.6
Public Administration	51.5	48.5
Total	48.3	51.7

Notes: Data Source: soep.v35, 2019. Gender share by industry.

cluded in the prediction model for men indicating an FTC-segregation. Included industries for women differ.[53] In the *Closing and Textile* and the *Health Service* industry, the larger fraction of workers is female. In the other three mentioned industries (*Synthetics*, *Electrical Engineering*, and *Wood, Paper, Print*) the share of women is below 40% but these variables are only included in the prediction model for women, which indicates an FTC-segregation for women in these industries. The results let suggest that it depends on the occupation, respectively the industry, and the gender, whether individuals are employed on a fixed-term basis. These variables and their interaction should be included in models analysing the FTC probability.

[53]For women, the following industries are included: *Synthetics*; *Electrical Engineering*; *Wood, Paper, Print*; *Clothing, Textile*; *Health Service*.

2.8 Discussion

Even though, shrinkage methods can be helpful tools in picking control variables, it is not per se clear that they pick the one and only correct combination of control variables. As Mullainathan and Spiess (2017) show with their example, LASSO leads to different models when run over multiple data partitions, and they can detect only few stable patterns. This is because LASSO is a data driven technique and such depends on the underlying data structure. If there are a lot of highly correlated variables, LASSO chooses one of them and omits the rest. I account for this aspect by applying the Elastic Net. Results show that only few chosen variables differ. Furthermore, I address this aspect by applying the adaptive LASSO technique and again results show only few differences in selected controls. Still, those methods suffer from inferential shortcomings and described in section 2.4. I use the Double Selection LASSO by Belloni et al. (2014a) and Belloni et al. (2014b) to circumvent this problem. But according to Wüthrich and Zhu (2020), even a double selection process yields no guarantee for selecting the correct control variables. They derive certain conditions under which both LASSO steps fail to select all relevant controls.[54] Considering these aspects, it is advisable to interpret the results with caution: just because the algorithm selects one of the control variables for a model there is no guarantee that it belongs in the "real" model.

Another aspect worth to consider when working with data driven selection methods is that they can only choose a variable that is available in the data. In this regard, more variables regarding the employer and the job would certainly increase the predictive power of the model. Still, not all variables are observable. This aspect leads to the next shortcoming: even though it might be possible to achieve causal results by the Double Selection LASSO, causality still depends on the conditional expectation function to hold as Angrist and Frandsen (2022) so convincingly demonstrate. To find a suitable identifying assumption for the problem at hand stays for further research and most probably requires a larger data set with more variables. Despite these limitations, the use of shrinkage methods offers valuable insights into various aspects of fixed-term contracts.

[54] See Wüthrich and Zhu (2020) for more information on this aspect.

2.9 Conclusion

Fixed-term contract workers can differ from permanent contract workers in terms of various characteristics. The question of this chapter was which characteristics of individuals are related to FTCs and might potentially determine them. The existing literature is limited to selecting variables based on economic knowledge and intuition. The goal of this chapter is to select models that give a satisfying prediction of the class belonging of FTC workers using the rich information the SOEP provides on an individual level and as a second goal to compare resulting coefficients.

I estimate logistic models with manually selected variables according to the literature and compare their performance to the data driven shrinkage models (LASSO and Elastic Net). Results of the benchmark models are mainly in line with the findings from literature (except for the significance of the female indicator in my benchmark models) but the predictive performance of the simpler benchmark models is poor: at a cut-off value of 0.5, benchmark models classify only 2.6-11.5% of FTC workers correctly. This indicates that there are some characteristics neglected that relate to fixed-term employment.

Comparing results from the LASSO and the Elastic Net regression to the benchmark models show that the shrinkage methods, using a much richer set of control variables, outperform the benchmark models: at a cut-off value of 0.5, they provide a sensitivity of nearly 32%. One might wonder whether this result stems from overfitting. I accounted for this problem by using a split sample and assessing the predictive performance with the validation data. The deviances and the deviance ratios of the LASSO and the Elastic Net are very close comparing the training and validation data indicating that they yield an out-of-sample prediction quite close to the in-sample prediction. The Elastic Net performs slightly better in terms of the deviance whereas the LASSO provides a marginally higher sensitivity. To asses the robustness of the chosen LASSO model, an adaptive LASSO is applied. This includes less variables related to satisfaction, fewer occupations and industries, but performs only slightly better than the original LASSO with a sensitivity of roughly 33%. This result indicates that the LASSO model is not free from selection errors but quite close to the adaptive LASSO and that it performs well.

What do those models include that the benchmark models neglect? The LASSO and the Elastic Net include more information about the household members, the household formation, and on the educational degree. They include more defined and differentiated variables about the current job, like industries, economic activities, and occupational levels, plus more information on whether the training fits the requirements of the job. LASSO and Elastic Net additionally make use of information on the past employment and unemployment experience. Some variables that are included might be surprising like variables related to the health status, the satisfaction with several aspects of life, and worries. Results are only descriptive and reverse causality cannot be ruled out. The inclusion of other than labour income components might be related to the lower wage rate of FTC employment. Both - Elastic Net and LASSO - do not include the female indicator.

As "inference task", I use a Double Selection LASSO model, where variables usually used in literature are forced into the model and LASSO selects additional variables in a multi-step procedure. With this procedure, I am able to compare coefficients of the benchmark models to coefficients of the "LASSO for inference"-models. Results show that coefficients of the benchmark model suffer from omitted variable bias. The female indicator, e.g. becomes insignificant (which is consistent with findings from the literature). Surprisingly, the full-time working experience is not significant which contradicts the assumption that an increasing working experience relates to a lower FTC probability.

The shrinkage methods do not select the female indicator and it turned insignificant using the Double Selection LASSO but the descriptive analysis suggests gender differences. Therefore, I estimate LASSO models separately for men and women. The subgroup analysis shows that the predictive performance is at a comparable level to the full-sample LASSO but included variables differ by gender. Only the LASSO model for women includes the age. This indicates a gender-age relation of the contract type which might be related to an increased FTC probability for women of certain age groups but this aspect is not further considered in this chapter. The negative signal of a dismissal by the former employer appears to affect the FTC probability only for women as well. For men, the occupational position seems to have an effect which is not present for women. Furthermore, included occupations and industries differ by gender. The chosen occupations are not all predominantly male or female. Hence, the inclusion is not related only to the gender-segregation in occupations but there could be a certain FTC-gender-segregation in occupations and industries. This aspect stays for further research.

One has to be very careful to draw conclusions from this descriptive analysis when making statements about their implications for the labour market actors. Still, results show a relation between certain characteristics of individuals and fixed-term employment. Considering the labour supply side, for employees who prefer more stable employment relationships, it is generally advantageous to increase their educational attainment and to search for employment in the private sector as being employed in public service is associated with an increasing FTC probability as is a lower education. The working experience seems to be less influential than proposed in literature. The inclusion of working hours and therefore their relation to FTC employment probability should be considered by employees. A higher work effort than provided by permanently employed is only beneficial to employees if this positive signal is compensated somehow. The inclusion of variables on job changes and breaks in employment show their relevance and should be considered by employees as well. Considering the labour demand side, for employers trying to fill vacant positions, it depends on what they are searching for: if the vacant position is designed such that educational requirements are lower or employees of younger age are preferred for the position, offering PCs might not be strictly necessary to fill the vacancy. If employers need to attract high qualified workers, they should consider offering permanent positions. Considering the perspective of policy makers: whether the directive to prevent misuse of fixed-term employment is met cannot be said from the results of this analyses. Still, especially the results of the subgroup analysis show a gender relation when it comes to certain occupations and industries. Furthermore, the potential relevance of (mental and physical) health measures should be of concern to governments. One would have to conduct a deeper and causal analysis to examine those aspect more closely. This aspect stays for further research. Generally, it might be beneficial to include more differentiated measures when it comes to analyse fixed-term employment.

Chapter 3

That Extra Edge - Disadvantages of Potential Mothers in Contract Duration

3 That Extra Edge - Disadvantages of Potential Mothers in Contract Duration

3.1 Introduction and Related Literature

It is well known that there are differences in labour market outcomes between men and women. Several studies show that women face disadvantages concerning their wages, their promotion probability, and employer's investments in their human capital. Less well analysed is the gender-related disadvantage of atypical employment or to be more specific, of fixed-term contracts.[1] With a growing number of fixed-term employees, the relevance of this topic increases. I contribute to the existing literature by providing evidence for a gender-related difference in the fixed-term employment probability of young women. I analyse whether potential mothers (women of childbearing age) have a higher probability of being employed on a fixed-term basis using changes in the legal regulations on parental benefits in 2007 as a natural experiment.

The changes in the legal regulations in 2007 decreased the financial disincentives of having children by linking parental benefits to the net earned income of employees and thereby increasing parental benefits for the majority of women. Before the reform in 2007, parental benefits were paid as a flat fee of 300 Euro for 24 months (or 460 Euro for 12 months), after the reform parental benefits range from 300-1800 Euro. The reform was supposed to increase the labour market attachment of women and to increase incentives for working women to have children. There is evidence that the reform had the intended effects: more women planned to return to their pre-birth employer after the reform (e.g. Bergemann and Riphahn (2011)) and the fertility increased (Stichnoth (2019) find a short-run fertility increase of 4%). Still, there might be (negative) side effects of this reform that were not analysed so far.

One such negative side effect could be an unequal treatment regarding the contract duration of groups with different absence risks. An increased fertility is likely to bring additional absences of employees in form of child-related leaves. When an employee becomes pregnant and gives birth, she will be absent for a certain period (maternity protection period and potentially parental leave). This can cause cost to the employer (inter alia additional cost of finding replacement). Seen from a purely economic perspective, an employer could take this risk into account when

[1] The term fixed-term contract (FTC) refers to a contract with limited duration. Fixed-term contracts are in contrast to permanent contracts that have an unlimited duration.

deciding to hire a female worker of childbearing age and be more likely to offer a fixed-term contract (FTC) instead of a permanent contract (PC). Employers do not have to renew expired fixed-term contracts but they would have to re-employ mothers when maternity leave ends under a permanent contract. For this re-employment the returning mother's job must be kept free. Thus employers could save the cost of additional absences using fixed-term contracts.[2] Following this argument, employers could prefer to use fixed-term contracts instead of permanent contracts if the probability of a potential pregnancy is high to decrease their risk.

Generally, fixed-term contracts hold advantages for employers but not necessarily for employees. Fixed-term contracts increase the flexibility of employers especially in countries with a strict employment protection legislation (EPL) like Germany. Among the EU15 member states in the period from 1995-2019, Germany has the fifth highest mean OECD indicator value for the EPL of collective and individual dismissals in regular contracts (mean indicator value of 2.6 compared to a mean value for the other states of 2.36, OECD (2020a)). Considering the mean values of EPL indicators for temporary contracts, Germany is only on the ninth highest place (with a mean value of 1.51 for Germany compared to a mean value of the other states of 1.99, OECD (2020b)). Those numbers indicate that the EPL for regular contracts in Germany is rather high and for temporary contracts it is comparably low. Hence, with fixed-term contracts employers are able to adjust the workforce more easily according to changes in labour demand. Furthermore, they can use fixed-term contracts as prolonged probation period and potentially avoid high dismissal costs from regular contracts if the employee does not meet the employer‘s expectations.[3] Results for a positive effect of a prolonged probation period are mixed. Analysing data from West Germany, Boockmann and Hagen (2008) find that the matching mechanism of fixed-term contracts works efficiently and employer-employee matches starting on a fixed-term basis are more stable. On the contrary, Blanchard and Landier (2002) detect negative effects on the turnover probability to permanent employment for France.

Turning to the employees' side, an increased flexibility of employers using fixed-term contracts is accompanied by a decreased security of employees. This should be compensated by a

[2] See Brown and Sessions (2005) p. 299 for a hint in this direction.
Additional absences after parental leave can result from the sickness of the child. If it is not excluded by the work contract, the employee may request a paid extra holiday up to 5 days (§616 German Civil Code, *Bundesgesetzbuch*). Otherwise the wage-replacement benefits are made by health insurances for ten days per child and parent but still the employee is absent for this period, which causes the cost of replacement to the employer.

[3] Information about the legal regulations of FTCs are in section 3.2. Legal regulations for scientific staff differ, because here a fixed-term contract is only paused and continues after return. As this group is excluded, this aspect is not further considered.

risk-premium in form of higher wages but there is evidence that fixed-term employees receive lower wages than their permanently employed counterparts (see Brown and Sessions (2005) for an international comparison).[4] Furthermore, Brown and Sessions (2005) find a lower job satisfaction of fixed-term employees in the United Kingdom and Chadi and Hetschko (2016) in Germany.[5] Following this argument, employees should prefer being employed on a permanent basis rather than temporary. Therefore, I argue that an increased probability of being employed on a fixed-term basis can be seen as a disadvantage. According to the German Federal Statistical Office, the fraction of fixed-term workers increased from 6.2% in 1995 to 8.5% in 2016 (Statistisches Bundesamt, 2020). As more workers are affected, it becomes increasingly relevant to address the issue of fixed-term contracts and analyse potential gender differences.

There is extensive evidence about gender gaps in the labour market: women receive lower wages, have a lower promotion probability[6], face lower employers' investments in their human capital[7], and are more likely to be employed on a fixed-term basis. One reason for gender-

[4] Booth et al. (2002) for example find a wage penalty for fixed-term workers for the UK, la Rica (2004) for Spain, Mertens et al. (2007) for Spain and Germany, Hagen (2002) for Germany, and Gebel (2009) for West Germany. According to la Rica (2004) and Mertens et al. (2007), results for Spain can mostly be explained by unobservable skill characteristics of employees rather than by a discrimination by employers. Findings for West Germany refer only to job entrants (Gebel, 2009).

[5] Chadi and Hetschko (2016) state that there can be a *honeymoon effect* of new employment relations increasing job-satisfaction in the very short-term but disguising the true effect of the contract type on job satisfaction which can lead to differing results. They control for this effect in their analysis and find that job insecurity is a main driver of the lower job satisfaction of fixed-term employees.

[6] In literature, different promotion obstacles are referred to as sticky floor, glass ceiling or glass door effects (see Dalla Chiara et al. (2014) for an overview). Russo and Hassink (2010) for example find evidence for a glass door effect defined as a lower probability of being employed in higher hierarchical levels concerning new hires in the Netherlands. Dalla Chiara et al. (2014) confirm this in their analysis of France, Italy, the Netherlands, and the United Kingdom with a slightly different definition. They refer to the term "glass door" for internal promotion obstacles in early career stages and provide evidence for a glass ceiling effect in form of an under-representation of women in managerial positions. By using data from a recruiting firm in the United Kingdom, Fernandez-Mateo and Fernandez (2016) analyse to what extend the gender-difference in managerial positions is a problem stemming from the supply- or demand-side. They find no evidence for a difference in hiring probabilities of men and women after the screening process but women are still less likely than men to be chosen to be a candidate for the recruiting firm in the very first step of selecting appropriate candidates. How do differences in promotion probability relate to child-related leaves? Equivalently to considerations about the wage differential, employers form beliefs about uncertain aspects of their (potential) employees. As women are more likely to leave the labour force for a certain period than men after childbirth, employers might take this risk into account. Using US data and analysing a reform on the maternity leave, Thomas (2016) finds that women of childbearing age are less likely to be hired after the introduction of the maternity leave and that this effect is more severe in firms with high training costs.

[7] Employers anticipate the risk of leaves by reducing their training expenses. This could partially explain the lower promotion probability. Analysing a reform on the extension of the parental leave from 18 to 36 months in Germany in 1992, Puhani and Sonderhof (2011) find that employer-arranged training decreases after the reform for women of childbearing age. Point estimates from the difference-in-differences approach suggest a reduction of up to 13.5 percentage points in training for young women compared to men (Puhani and Sonderhof (2011), p. 750).

related differences is the lower labour market experience of women due to realised child-related absences, but even without absences differences exist (see e.g.Meurs et al. (2010)).

Following standard human capital theory there is lower accumulation of human capital because of the interruption. Focussing on the wage differential, this could lead to lower wages for women who left the labour force for childrearing (see e.g. Mincer and Polacheck (1974), Gangl and Ziefle (2009)).[8] According to Budig and England (2001) and Fernández-Kranz et al. (2013), other reasons - beside the lack of experience - that could explain the wage differential are a selection into family-friendly (part-time) work or lower paying occupations, or a lower productivity. But there still remains an unexplained part which could be caused by employer sided discrimination (Budig and England (2001)). This goes in line with the findings presented in this chapter: controlling for the labour market experience the gender difference in contract duration becomes smaller but it still remains.

One reason for employer sided discrimination stated in literature is based on the problem of imperfect information. Even if there is no taste based discrimination, there could be statistical discrimination. Employers do not have perfect information ex ante and therefore form beliefs about the characteristics of the individuals they consider to employ driven by the beliefs about the group they belong to (Darity and Mason (1998)).[9] Labour market outcomes are linked and cannot be considered each on its own, e.g. average wages can differ by contract type. If there is a wage gap because of the contract type and a higher probability of women to be employed on a fixed-term basis, the contract type could explain part of the gender-wage gap.

There is suggestive evidence that gender-related discrimination is apparent in form of the contract type as well. Petrongolo (2004) finds in her descriptive analysis that the share of female FTC workers is higher for all countries of the EU15 (except for Denmark) and being married (without children) increases the probability of having an FTC for women (significant for the United Kingdom, Finland, Denmark, the Netherlands, and Belgium). The author states that systematic differences in the offered contract type can be seen as some form of gender discrimination (Petrongolo (2004)). The increase in the FTC probability is not significant for Germany in her analysis which contrasts my findings. Berton and Garibaldi (2012) confirm that employers anticipate the risk of leave by offering fewer permanent contracts to women based on their

[8] Most analyses show that the wage gap between men and women decreased in the last decades but is still observable (Weichselbaumer and Winter-Ebmer (2005); Blau and Kahn (2007)). Furthermore, wage differentials differ by country and are high for German-speaking countries compared to Denmark, Sweden, the United States, and the United Kingdom (see e.g. Gangl and Ziefle (2009) and Kleven et al. (2019)).

[9] This could explain the findings of Meurs et al. (2010) who detect a gender-wage differential comparing men and women without any child-related interruptions for France.

theoretical considerations and their empirical analysis of Italian data. They find that women in Italy have a higher probability of being "atypically" employed (including not only part-time work but also FTCs). Following the "stepping stone hypothesis" this probability is higher for younger age groups and declines with age. Cipollone et al. (2012) conclude from their analysis of women in the EU15 member states that the increase of FTCs for women is a transition phase to permanent employment because the probability of holding an FTC declines with age. As their analysis concentrates only on women, the aspect of gender differences is not accounted for.[10] Dalla Chiara et al. (2014) consider gender differences and confirm the finding of Petrongolo (2004) for Italy. Their results suggest that the gender differences in contract duration is highest for the youngest age group. Results from literature show that women are more likely to be employed on a fixed-term basis in several countries. As legal regulations differ across countries, my analysis of gender differences in Germany contributes to this strand of literature. Furthermore, if the gender difference is more severe after the reform, this would suggest that there are so far unconsidered negative side effects of the reform on parental benefits. My results provide evidence that the difference in contract duration is not purely driven by the age of individuals but also relates to belonging to the risk group of young women (potential mothers).
Employers should perceive the probability of a child-related leave higher for women in younger age groups. As women are more likely than men to leave the labour force after childbirth for a certain period, the perceived risk of a child-related leave should be higher for women of childbearing age than for men in the same age-group. There is evidence that this is the case: comparing homo- and heterosexual women in Belgium, Baert (2014) finds that young heterosexual women, for which the risk of pregnancy is higher, have a lower general hiring probability. Becker et al. (2019) confirm this for German speaking countries and part-time employment. Their results clearly suggest a relation between the signals of women about the risk of child-related leaves: in terms of the employment probability in part-time jobs, young, married women without children face a disadvantage compared to young, single women.[11] Petit (2007) finds a general hiring discrimination against young women in France, which is even higher for permanent contracts. As an explanation, he suggests that employers want to minimise the costs of child-related absences. Fernández-Kranz and Rodríguez-Planas (2011) confirm this result for Spain, where they find that an increased employment protection leads to a higher preference

[10] Bryson (2004) analysed whether FTCs could be a stepping stone for women in academia in the UK; the author finds that FTCs creates a trap for both genders. As academic staff is excluded from my analysis because of the another legal basis in Germany, that aspect is not considered here.

[11] Results were not found for full-time jobs.

of employers to employ men of childbearing age on a permanent basis but offering FTCs to women of childbearing age. The analysis of Fernández-Kranz and Rodríguez-Planas (2011) is close to my considerations as they analyse the effects of a Spanish policy reform in 1999 on the probability of being employed on a fixed-term basis. The reform allowes parents to reduce their work time until their children are 7 years old and make dismissals invalid if the reason was the intended reduction of work time of the employee. Therefore, the reform increased the employment protection but only for those with a PC. They found that the likelihood of having a PC is reduced by 18% for the risk group (women of childbearing age) and the likelihood of having an FTC is increased by 30% ((Fernández-Kranz and Rodríguez-Planas, 2011), p. 4). Hence, they find that the policy reform had negative side effects: it was intended to support parents but neglected effects from an increased employment protection in one contract type (PC) on other contracts types (FTC) in a flexible labour market. Equivalently, my results show negative side effects of a reform that was supposed to support parents with increased parental benefits but led to an increase in gender-differences in contract types at the same time.

Results from the literature indicate that there is a hiring discrimination against women of childbearing age and differences in the contract type because of their higher risk of leaves. Still, the presented results based on considerations of different countries are not necessarily applicable to Germany as legal regulations regarding maternity protection, employment protection, and therefore the determinants of employers' preferences about contract durations differ. My analysis contributes to the literature by finding a significant gender effect on the contract type for Germany using data from the Socio-Economic Panel (SOEP) and a legal change of parental benefit regulations in 2007 as natural experiment in a difference-in-differences approach. With the reform in 2007, the parental benefits were made dependent on the amount of the pre-birth net earned income and thus increased for the majority of women. Parental benefits range from 300 to 1800 Euro for 12 (14) months compared to 450 Euro for 12 months prior the reform (for more information see section 3.2).

First, I analyse potential determinants of the probability of being employed under an FTC descriptively as basis for the further analyses. Second, I apply a difference-in-differences (DiD) approach for individuals of childbearing age using women as treatment and men as control group. Thereby I consider the subgroups of individuals with children, without children, and married individuals without children, as I expect that family planning and therefore the probability of having (additional) children differs between those subgroups. I find that young women are significantly more likely to be employed on a fixed-term basis than men after the reform. This effect seems to be driven by the subgroup of young individuals without children where point estimates suggest an increase in the probability of an FTC of 2.3 percentage points. The considered reform links parental benefits to the pre-birth income, which is why I assume that the inciting effect of the reform differs by the income level. Therefore, I apply the DiD approach to different income subgroups and find that there is a probability increasing effect for young women without children in the second lowest income group of 3.8 percentage points.

If the increased probability is a form of gender-related discrimination against women of child-bearing age, young women should be more affected than men and older women. I test this using a difference-in-difference-in-differences (DDD) approach using young women as treatment and men and older women as control group. I find that women of childbearing age without children are significantly more likely than men and older women to be employed on a fixed-term basis after the reform. Point estimates suggest that their probability increased by 3.1 percentage points.

My results are robust to the following tests: a formal "test" of the parallel paths assumption, including placebo-reforms, using a lower number of pre- and post reform periods, and using a broader definition of the childbearing age. Furthermore, I restrict the sample to new hires, such employment relations that last less than one year in the respective survey year. The reform effect on the probability of being employed on a fixed-term basis is still positive and significant. The robustness tests indicate that DiD-results for the subgroup of individuals of childbearing age are robust. Hence, I find evidence for a gender-related difference in the contract duration for potential mothers.

The remainder of this chapter is organised as follows: In the next section, I give an overview over the legal regulations of fixed-term employment in Germany, regulations regarding parental leave in Germany, and the changes implemented by the reform in 2007. In section 3.3.1, I present the empirical strategy and the data. Following the descriptives in section 3.3.2, I discuss the results in section 3.4 and their robustness in section 3.5. The last section concludes.

3.2 Background

Fixed-term employment in Germany

As described in chapter 2 of this thesis, there are two main types of fixed-term contracts in

Germany: Fixed-term contracts with factual reasons and without factual reasons. The legal regulations regarding the allowed duration and the number of consecutive contracts differ between those two types.

For fixed-term contracts with factual reasons, there are some causes stated in the Part-Time and Fixed-term Employment Act §14(1) ("TzBfG", *Teilzeit- und Befristungsgesetz*). Factual reasons are (among others): the need for the work is only temporary, the fixed-term contract follows directly vocational training or studies, contracts for replacing workers, when the specific nature of the work performance justifies the FTC, if the FTC is used for probation, reasons relating to the person of the employee justify the FTC, if the employee is remunerated from household funds that are linked to a fixed-term employment relationship, and if the time limit is based on a court settlement. Besides those stated reasons, reasons that are equivalent are sufficient as well. Neither the number of consecutive FTCs based on a factual reason nor the maximal duration is limited.

On the contrary fixed-term contracts without factual reasons are subject to different rules. FTCs without factual reasons are only allowed in three cases based on the Part-Time and Fixed-term Employment Act §14(2)-(3) ("TzBfG", *Teilzeit- und Befristungsgesetz*): First, if the employment is calendared (in German: *kalendermäßig*), meaning that FTCs are only allowed for a total duration of two years and three consecutive contracts if there was no employment relationship of the contracting parties in the past. Second, FTCs without factual reason are valid in the first four years after company foundation. In this time, an employee can be hired on a fixed-term basis for four years and multiple consecutive contracts are allowed. Third, an employer can choose an FTC if the employee is older than 52 years and was not employed for the last four months. In this case, fixed-term employment can be for maximal five years and multiple consecutive contracts are allowed.

FTCs demand a written contract. According to the Part-Time and Fixed-term Employment Act §15 ("TzBfG", *Teilzeit- und Befristungsgesetz*), the employment relationship ends when the time set in the contract expired or when the purpose of the employment relationship has been achieved. If the employment relationship continues after the expiry date with the knowledge of the employer, an FTC turns into a PC.[12]

[12]Unfortunately, the data used does contain neither information on whether contracts are with or without factual reasons nor about the real duration of the current contract.

Maternity protection and parental leave in Germany

Maternity protection and parental leave periods in Germany are rather long compared to other countries.[13] Women may not work 6 weeks before and 8 weeks after they give birth (§3 Maternity Protection Act, "MuSchG", *Mutterschutzgesetz*). After this period of maternity protection, parents can take parental leave. In this period, their income is partly replaced by parental benefits and a dismissal is only possible in specific cases (§18 Legislation on Parental Allowance and Parental Leave, "BEEG", *Bundeselterngeld- und Elternzeitgesetz*). Several reforms changed the time span of parental leave and the amount of the parental benefits since the late seventies.[14] In 2001, the parental benefit was linked to the duration of the parental leave for the first time. By taking only 12 months of parental leave, it increased from around 300 Euro (for taking 24 months) to 460 Euro (for taking 12 months) per month. Still the amount of parental benefits was dependent only on a positive labour income of parents but not on the amount of this income. This changed with the reform in 2007.[15] With this reform parental benefits became dependent on the amount of the income and the general entitlement period for parental benefits decreased from 24 to 12 (14) months for children born after January, 1st 2007. Parents can share the time of the parental leave and it increases up to 14 months if the father takes at least 2 months of the parental leave. The amount of the parental benefits now depends on the average net earned income 12 months prior to birth and ranges from 300 to 1800 Euro according to §2ff Legislation on Parental Allowance and Parental Leave (*BEEG*). Figure 3.1 displays the percentages for the different incomes. The minimum amount of parental benefits is 300 Euro, i.e. individuals with a monthly income below 300 Euro receive more than 100% of their pre-birth income. If they earned between 301 and 360 Euro, they receive 100% of their pre-birth income. The benefit decreases from 100% to 67% by 0.1 percentage point per 2 Euro for the income group from 361-1000 Euro. For incomes between 1000 Euro and 1200 Euro, the benefits are 67% of the pre-birth income. Benefits decrease by 0.1 percentage point per 2 Euro for incomes of 1201-1240 Euro resulting in a percentage of 67-65%. For incomes above 1240 Euro and lower than around 2770 Euro, individuals receive benefits of 65%. For incomes above 2770 Euro, the

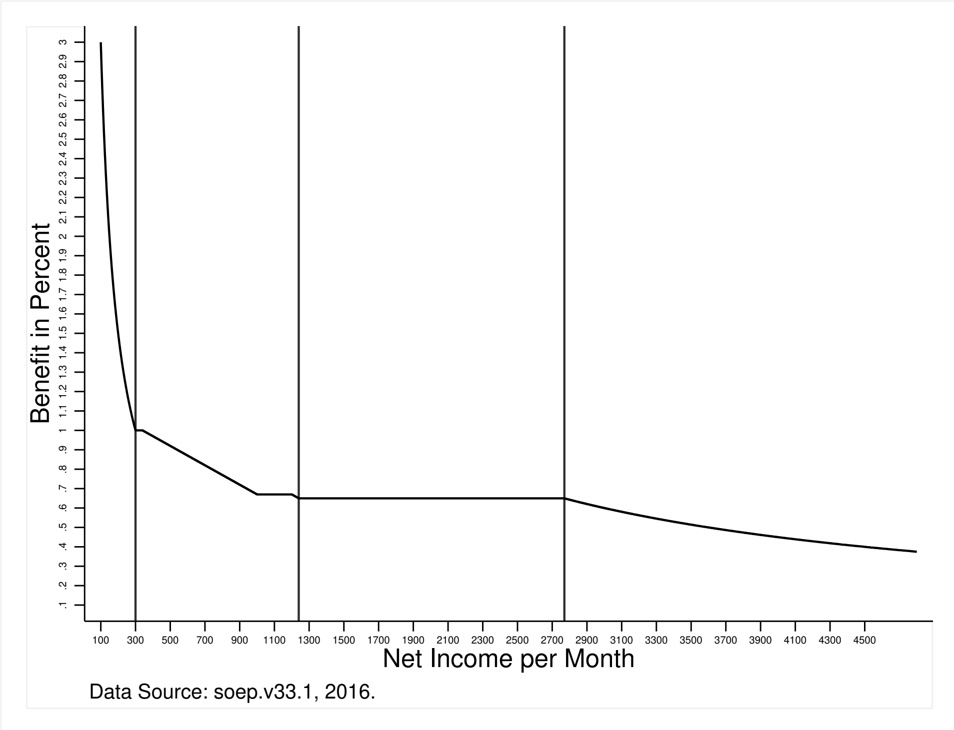
[13]Considering OECD countries in 2016, Germany had the third longest period of job protected parental leave, following Poland with around 183 and Spain with 150 weeks. OECD Stat Data extracted on 25 Mar 2019 08:21 UTC (GMT) from OECD.Stat.

[14]See Puhani and Sonderhof (2011) for a detailed overview. In 1992, the maximal duration of the parental leave increased from 18 to 36 months. The duration of the parental leave stayed the same in 1993 (36 months) but since 1993 parental benefits of around 300 Euro were paid for 24 months.

[15]§§8a-8d *Maternity Protection Act* were replaced by §§15ff *Legislation on Parental Allowance and Parental Leave*.

upper limit of 1800 Euro applies and the effective percentage of income decreases accordingly.

Figure 3.1: Parental Benefit in Percent of Income



The reform intended to increase incentives for employed women to give birth by decreasing the opportunity cost of having children, to incite mothers to stay at home for childcare for 12 months (also to give an incentive for fathers to take parental leave), and to increase labour market attachment of women. As results from literature suggest, the intended effects were met: Stichnoth (2019) and Raute (2019) find an increased fertility especially for women with higher income. Stichnoth (2019) find that it would decrease the number of births 5 years after the reform by 24000 (corresponds to 4%) if the parental benefit regulations of prior 2007 were in place (Stichnoth (2019), p.11). Raute (2019) applies a DiD approach analysing fertility effects of the reform in 2007 and find as well that 5 years after the reform fertility increased by about 4%. For the highest educated group (tertiary education), she even finds an increase of up to 23% (Raute (2019), p. 203). With an increased fertility, employers should perceive the risk of pregnancy and child-birth related leaves for women of childbearing age as higher. From the results of their simulations, Stichnoth (2019) deduce that the fertility increasing effect of the reform is stronger for first births. This goes in line with results from my analysis. If the perceived risk of employers for potential mothers (women of childbearing age without children) is higher because of their larger increase of fertility after the reform, this should be reflected by an increased probability of being on a fixed-term contract for women in this risk group.

Besides the increased fertility, the reform indented to strengthen the labour market attachment of women. Bergemann and Riphahn (2011) find that the fraction of women who plan to return to work after 12 months of parental leave increases after the reform. Kluve and Tamm (2013) confirm this with their result of a decreased employment probability for women after the reform for the first 12 months after giving birth and an increased employment probability after 12 months. Contrary to my considerations, they concentrate on effects of the reform on the employment probability of women. The contract type is not considered in their analyses. Kluve and Schmitz (2014) analyse medium-term effects of the reform and find that the fraction of women that return to their pre-birth employer after 12 months of parental leave increased after the reform. Furthermore, their results indicate an increased probability of having a permanent contract after the reform. In all three analyses, mothers who gave birth after the reform act as treatment and mothers who gave birth prior the reform act as control group and gender differences were not considered.[16] Hence, results from literature let suggest that the positive effects that were to be achieved with the reform have indeed occurred. Still, in contrast to my analysis, those analyses do not focus on the gender-differences in the employment probability in different contract types. I concentrate on this gender-related difference as a negative side effect of the reform to detect a potential disadvantage for women.

What consequences can arise from this reform regarding employers‘ perceptions? With an increased financial incentive, more people could decide to have children (which was intended by the reform and happened). Following this increased incentive employers might perceive the risk of a downtime due to maternity protection periods and parental leave as higher than prior the reform. If this is the case, the probability of being employed on a fixed-term basis for women would increase after the reform.[17] The incentive effects of this reform should vary by the pre-birth income. Therefore, I analyse the subgroups of different income levels in chapter 3.4.1.

[16] The considered prior-reform periods are restricted to 2005/2006.

[17] I do not expect that the probability increase for men is noteworthy as men probably in most cases take only two months of parental leave after the first birthday of the child. See Kluve and Tamm (2013) for results about the length of fathers‘ parental leave and the related childcare involvement of fathers. An absence of two months can be more easily covered by employers than an absence of 12 months. Therefore, I do not expect that there would arise high additional costs for a replacement in cases of short absences that would affect the decision of employers.

3.3 Data and Methodology

3.3.1 Empirical Strategy and Data

The main question is whether women are more likely than men to be employed on a fixed-term basis. Analysing this question, there might occur endogeneity problems, e.g. due to a self-selection into fixed-term employment that differ by gender. For example, there could be an unobserved gender-related difference in preferences for flexibility. To analyse gender differences in the probability of being employed on a fixed-term basis with a causal claim, I apply a DiD approach with women of childbearing age as treatment and men in the same age group as control group using the reform in 2007. The regression equation is:[18]

$$FTC_{it} = \beta_0 + \beta_1 \cdot female_{it} + \beta_2 \cdot reform_{it} + \beta_3 \cdot (female_{it} \times reform_{it}) + X'_{it}\gamma + u_{it} \qquad (3.1)$$

The binary dependent variable FTC_{it} denotes whether individuals are employed on a fixed-term basis in year t. β_1 gives the estimated mean difference of the probability of being employed on a fixed-term basis for men and women before the legal changes in 2007. β_2 captures the time effect for men. β_3 is the coefficient of interest and is defined as:

$$\begin{aligned}\hat{\beta}_3 = &\{E[FTC_{it}|female = 1, reform = 1, X_{it}] - E[FTC_{it}|female = 1, reform = 0, X_{it}]\}\\ &-\{E[FTC_{it}|female = 0, reform = 1, X_{it}] - E[FTC_{it}|female = 0, reform = 0, X_{it}]\}\end{aligned}$$

$\hat{\beta}_3$ gives the expected change in the probability of being employed on an FTC for women comparing before and after the reform in 2007 minus the expected change in the probability of being employed on an FTC for men. If it is significant, it indicates that the change in the probability was different for men and women.[19] Control variables are described in the next section. Standard errors are clustered at the individual level.

It might be the case that not only young women are more likely to be employed on a fixed-term basis than young men but that this holds true for older women as well. Therefore, I analyse whether the reform had an effect on women of childbearing age compared to men in the same

[18] For simplicity reasons, I use a Linear Probability Model although the dependent variable is binary. Results from the non-linear Model (Probit) for potential mothers are comparable to results from the LPM though marginal effects are slightly lower. Results can be obtained from the author upon request.

[19] I analysed the subgroup of older individuals as well. As the parallel paths assumption is not fulfilled for older individuals and the placebo-test shows significant effects of placebo reforms, results from the regressions are not reliable and not presented in this chapter but are available on request.

age group and older men and older women by applying a DDD approach. The regression equation is defined as:

$$\begin{aligned} FTC_{it} =& \delta_0 + \delta_1 \cdot female_{it} + \delta_2 \cdot reform_{it} + \delta_3 \cdot cbage_{it} \\ & + \delta_4 \cdot (reform_{it} \times female_{it}) + \delta_5 \cdot (female_{it} \times cbage_{it}) + \delta_6 \cdot (reform_{it} \times cbage_{it}) \\ & + \delta_7 \cdot (female_{it} \times reform_{it} \times cbage_{it}) + X_{it}'\gamma + u_{it} \end{aligned} \tag{3.2}$$

where δ_7 is the coefficient of interest. The OLS estimate of this coefficient can be expressed as:

$$\begin{aligned} \hat{\delta}_7 = & (E[FTC_{it}|female=1, reform=1, cbage=1, X_{it}] - E[FTC_{it}|female=1, reform=0, cbage=1, X_{it}]) \\ & -(E[FTC_{it}|female=0, reform=1, cbage=1, X_{it}] - E[FTC_{it}|female=0, reform=0, cbage=1, X_{it}]) \\ & -(E[FTC_{it}|female=1, reform=1, cbage=0, X_{it}] - E[FTC_{it}|female=1, reform=0, cbage=0, X_{it}]) \\ & -(E[FTC_{it}|female=0, reform=1, cbage=0, X_{it}] - E[FTC_{it}|female=0, reform=0, cbage=0, X_{it}]) \end{aligned}$$

With this approach, I get the change in the probability resulting from the reform for women of childbearing age and net out the change in the probability for men of childbearing age and men and women in the older age group. If this coefficient is significant and positive, it indicates that the reform resulted in a higher probability of being employed on a fixed-term basis for young women.

For results from the DiD and DDD approach to be valid, the main assumption that needs to hold is the parallel paths assumption. It requires a constant evolution of the difference between the treatment and control group outcomes had there been no treatment. The identifying assumption using young men as control group for the DiD and men and older women as control group in the DDD is discussed below and analysed formally in section 3.5.

I use the data from the German Socio-Economic Panel (SOEP).[20] I restrict the considered period to the years 1995 to 2016 and consider employed individuals in the working age defined as 20 to 55 years.[21] The childbearing age is defined as 20-35 as in Puhani and Sonderhof (2011). As a robustness test, I extend the childbearing age to 20-40 in section 3.5.2 to account for an increase in the age of first-birth over the considered period. I exclude individuals in training, apprenticeship, those who do their doctorate, and military workers as those are in most cases

[20] Socio-Economic Panel (SOEP), data for years 1984-2016, version 33, SOEP, 2017. Wagner et al. (2008).

[21] I start with the year 1995 because in the early 1990s there were several reforms of parental leave legislation that could bias my results.

employed on a fixed-term basis in Germany disregarding their characteristics. Self-employed individuals and individuals with a monthly income below 100 Euro are excluded.

The dependent variable FTC_{it} is a dummy variable that indicates whether individuals are employed on a fixed-term or a permanent basis in year t. The question at hand is whether employers base their decision of employing an individual fixed-term or permanently on whether someone belongs to the risk group. Therefore, one can argue that the sample should be restricted to new hires in the respective survey year, to see the effects of the reform on new contracts directly.[22] There are two main reasons, why I use the whole sample of fixed-term and permanently employed individuals instead of only new hires in this analysis: First, the number of new hires in the data at hand is very limited. Table 3.1 shows the number of women and men who were newly hired on a fixed term basis in the period before and after the reform in 2007. For the 11 years prior to the considered reform (1995-2006) there are 697 (640) women (men) newly hired and for the 9 years after the reform there are 1825 (1383) new hires in fixed-term contracts. As I use a rich set of control variables (discussed below) the number of observations might be too small to provide reliable results without reducing the model. Nevertheless, to account for this aspect, I present results of the analysis for the subgroup of newly hired workers in section 3.5.3 using a reduced model. Second, with a sample restricted to new hires there could be a sample selection I cannot account for, as the reasons for changing one's job can be manifold. Hence, there might be a selection processes into the group of newly hired individuals that cannot be accounted for. Therefore, I analyse the stock of all employment relations and control for the tenure as discussed below. With this approach, I am still able to analyse whether the probability of a fixed-term employment relationship is higher after the reform.

Table 3.1: Number of New Hires by Gender and Reform

	Women (treated)		Men (control)	
	Prior Reform	After Reform	Prior Reform	After Reform
New Hires	697	1825	640	1383

Data Source: soep.v33.1, 2016.

To answer the question whether women are worse off than men in terms of their contract duration, I use men in the same age group as control group. In table 3.2 the number of men and women working in the different contract types are displayed as well as the related fractions.

[22] As stated, the data at hand contains no direct information on whether the FTC is with or without factual reason or about the expiry date of the contract.

Considering the whole sample, the fraction of women working in a fixed-term contract is with 11.0% higher than the fraction of men (8.4%). Considering only individuals of childbearing age, the fraction of FTC workers is higher for both genders which indicates that the contract type depends on the age. Still, the fraction of young women in FTCs is higher than the fraction of young men (16.9% vs. 14.7%). Considering this subgroup in the period prior the reform (1995-2006) and after the reform (2007-2016), the fraction of women and men increased after the reform indicating a certain time trend for both genders. Hereby the increase in the fraction is with 8.7 percentage points higher for women than for men with 7.6 percentage points.

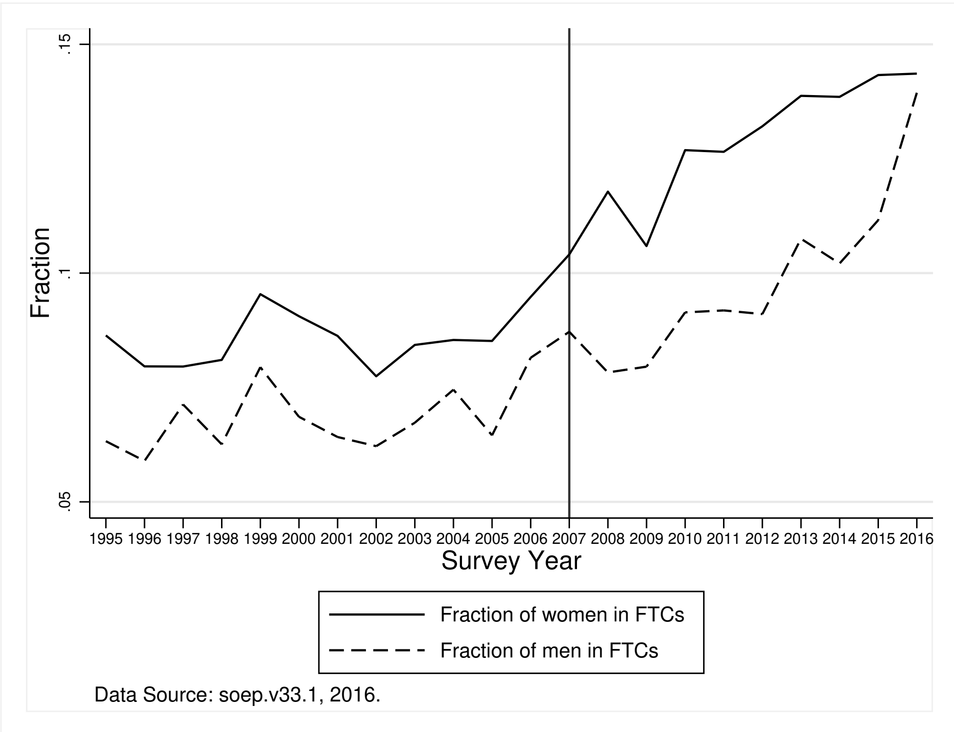
Table 3.2: Numbers of Observations for Men and Women in FTCs and PCs

Gender	Contract Type PC		FTC		Total	
	No.	%	No.	%	No.	%
Male	86,616	91.6	7,933	8.4	94,549	100.0
Female	80,897	89.0	10,018	11.0	90,915	100.0
Total	167,513	90.3	17,951	9.7	185,464	100.0
Subgroup Childbearing Age						
Male	26,422	85.3	4,556	14.7	30,978	100.0
Female	23,307	83.1	4,730	16.9	28,037	100.0
Total	49,729	84.3	9,286	15.7	59,015	100.0
Prior Reform						
Male	15,146	88.7	1,923	11.3	17,069	100.0
Female	12,556	87.4	1,815	12.6	14,371	100.0
Total	27,702	88.1	3,738	11.9	31,440	100.0
After Reform						
Male	11,276	81.1	2,633	18.9	13,909	100.0
Female	10,751	78.7	2,915	21.3	13,666	100.0
Total	22,027	79.9	5,548	20.1	27,575	100.0

Notes: Data Source: soep.v33.1, 2016. Distribution of gender and contract type.

To show the time trend graphically, I plot the fraction of individuals working in the different contract types by gender against the survey year in figure 3.2 for all individuals and in figure 3.3 for individuals of childbearing age. Without controlling for additional characteristics, the fraction of women in fixed-term contracts is higher than the fraction of men in fixed-term contracts. There is a general increase of the fraction of FTC workers for both genders over the considered period. The difference in the fractions of men and women seems to be bigger after the reform. This is more pronounced for individuals of childbearing age (figure 3.3): The fraction of FTC workers before the reform in 2007 evolves relatively equally for men and women. After the reform, there is an increase in the gap between men and women detectable. Both figures show an upward trend for fractions of male FTC workers from 2015 onwards, and the data suggest that this is caused exclusively by individuals without the German nationality. Still, those are not excluded from regressions.[23] Differences in fractions are displayed in figures B.1 and B.2 in Appendix B.5. The difference appears rather stable for both age groups prior the reform and increases after 2007. The difference for individuals of childbearing age is more volatile but one can observe an increase in the difference after 2007 as well.

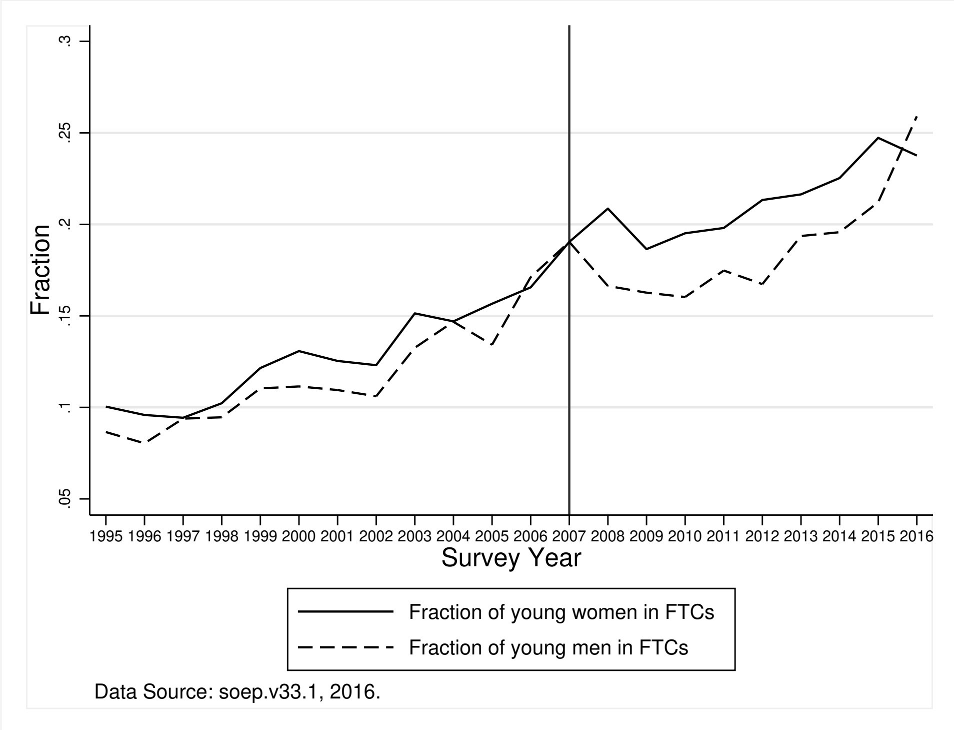
Figure 3.2: Fraction of FTC Workers by Gender for Both Age Groups



This indicates that the reform in 2007 might have had different effects on men and women which are more pronounced for individuals of childbearing age. Without controlling for additional characteristics, women's relative employment in fixed-term contracts seems to have increased after the reform. To analyse whether this increase is statistically significant and still observable after controlling for additional covariates, I apply a DiD approach in section 3.4.1. At a first glance, fractions for FTC workers for men and women follow a rather similar trend prior the reform, which is why there is no evidence that the parallel paths assumption could be violated using men as control group. Nevertheless, I additionally analyse the parallel paths assumption

[23]Graphs including only individuals with German nationality are available upon request.

Figure 3.3: Fraction of FTC Workers by Gender for Individuals of Childbearing Age

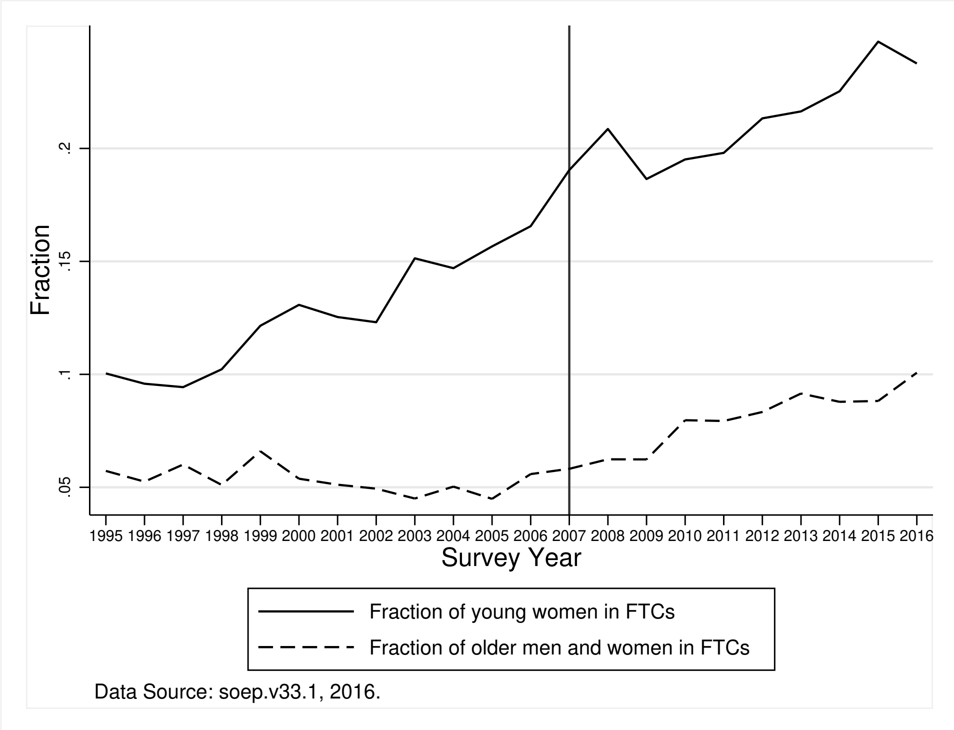


formally, as there are more than one pre- and post-reform periods and I am able to control for additional characteristics in a formal analysis.

Considering the DDD approach, I compare effects for women of childbearing age and men of childbearing age, older men and older women. One could question whether the identifying assumption is fulfilled as there might be general differences in the life planning of different generations. Figure 3.4 shows the fraction of women of childbearing age (solid line) and the fraction of older men and women (dashed line) in fixed-term contracts. The fraction of female FTC workers of childbearing age is much higher compared to the older age group. Focussing on the fraction of older FTC workers, figure 3.4 shows a relatively flat evolution over time. There is a slight increase which is more pronounced in 2009/2010. After 2010, there is no steep increase visible for older FTC workers. The increase might be related to the financial crisis 2008/2009 as employers might have preferred a higher flexibility shortly afterwards. Nevertheless, the relatively stable fraction of FTC workers in the older age group suggests that the preference for higher flexibility has weakened over time. The increase for women of childbearing age is much steeper and the difference of both groups is increasing over time (see as well figure B.3, Appendix B.5). The visual inspection shows no evidence that there were factors other than the considered reform that substantially changed the trend in the evolution of the fraction of female

FTC workers of childbearing age compared to older FTC workers. Therefore, I consider the group including also older men and women as valid control group for the DDD approach.

Figure 3.4: Fraction of FTC Workers by Gender - Compared to Older Men and Women



Turning from the dependent variable to the control variables used in regressions, X_{it}, I include various personal and job related characteristics: Focusing on personal characteristics, I control for the age and it's squared to account for differences based on the exact age in the considered age group. Furthermore, I include the education of individuals with respect to high school, the marital status, the number of persons in the household, the employment level of the partner, and the number of children.[24] Married individuals might perceive a higher security from not bearing the full responsibility of earning the household income and might be therefore more willing to accept a fixed-term contract with a lower job security. On the downside, individuals who are single might feel the need to take any job to ensure the household income. Similar considerations hold true considering the employment level of the partner. If the partner is unemployed, the individual bears the full responsibility for the household income and might be more likely either to take any job or to take only the most secure form of employment. If the partner is employed on a permanent basis, the pressure to have a high job security might be

[24]For the subgroup of individuals without children, this variable is not included. The base category for this variable for the subgroup of individuals with children is *1 to 3 children*.

lower for the individual. The earned and required household income could vary with the number of household members, which is why this variable is included. The number of children might be related to the time, individuals have to devote to child-care responsibilities. A binary variable for living in West Germany is included as the social recognition of working mothers in East Germany might have persisted and their labour market attachment might be perceived higher by employers resulting in a different probability to employ on a fixed-term basis.

Turning to characteristics of the employment history, I control for the full-time working experience and it's squared, the part-time working experience and it's squared, a binary variable for having been dismissed by the former employer, and a variable for the previous number of years in FTCs. The working experience is essential for the analysis of differences between men and women as the classical role model might still persist: Women are more likely to take care of the household and children and work therefore part-time or have a lower working experience due to child related leaves. Furthermore, FTCs are partly used as a prolongation of the probation period in the case of negative or uncertain signals of employees (see e.g. Hagen (2002)). If a lower working experience is such a negative signal, it should have an influence on the probability of being employed on a fixed-term basis. This argument holds as well for the indicator variable for having been dismissed by the former employer and the number of years in FTCs, which both act as negative signal.

Considering job related characteristics, I include the occupation on a 1-digit level[25], the occupational position, the required training for the job, and the firm size. I control for the occupation and the occupational position to capture a potential gender-related segregation. It might be the case that one gender is more likely to be employed in some occupations or positions, like for example women in nursing professions, and that it is additionally more likely that individuals are employed on a fixed-term basis in these occupations. Results from literature show evidence for this gender-related segregation, e.g. Riach and Rich (2006) find hiring discrimination against both genders dependent on the gender profile of the occupation for the UK. Alonso-Villar and Del Río (2010) find for Spain that segregation of female workers is higher than of men. The firm size is included to account for the employer's capability to replace employees in the short run. Furthermore, the contract type could vary with the required training and workers in jobs

[25] Managers, Professionals, Technicians and Associate Professionals, Clerical Support Workers, Services and Sales Workers, Skilled Agricultural, Forestry and Fishery Workers, Craft and Related Trades Workers, Plant and Machine Operators and Assemblers, Elementary Occupations.
Excluded are those in military service as contracts in the military service are most likely to be on a fixed-term basis disregarding personal characteristics.

with a low training requirement could be easier to replace. A binary variable for working in public service is included as well to account for potential differences in the fixed-term employment probability in the public and private sector. The next section shows descriptive results for the stated control variables.

3.3.2 Descriptives

To compare the treatment and control group in terms of their observed characteristics, the mean, the standard deviation, and the number of observations for several observables used in the regressions are displayed in table B.1 (Appendix B.1) for men and women of childbearing age separately for the years 1995-2006 (prior the reform) and 2007-2016 (after the reform).

Regarding personal characteristics, descriptives for age, educational attainment, marital status, employment level of the partner, state of residence, number of persons in the household, and number of children are displayed. Comparing the pre- and post-reform sample individuals after the reform seem slightly better educated.[26] The fraction of single individuals increases after the reform. This can be observed also by considering the variable for the partner‘s employment level for women.[27] The fraction of those with one to three children increases after the reform for both genders indicating an increased fertility after the reform.

Regarding the work history of individuals, the mean full-time and part-time experience are considered as well as the mean years in FTCs and the fraction of individuals who were dismissed by their former employer. The latter two variables can form a negative signal to potential employers which is why I include them (e.g. Hagen (2002)). The number of years in FTCs increases for both genders after the reform and is higher over the whole considered period for women compared to men.

To control for firm and job characteristics, I consider occupation, firm size, and whether individuals are employed in public service. I use occupations at a 1-digit level. If there is a gender segregation and if it is more likely to be employed on a fixed-term basis in certain occupations, one reason for women being more likely to have an FTC could be that it is more likely to be employed under FTCs in “female occupations”. As fractions of men and women differ in the considered occupations, there seems to be a certain gender-relation in occupational choices.

[26] For the educational attainment, I use a categorical variable that indicates whether the individual has a degree lower than high school, high school, or higher than high school.

[27] For the employment situation of the partner, I used the partner identifier and the employment level of individuals to generate a variable with categories of having no partner, partner is unemployed, partner is employed fixed-term, and partner is employed permanently.

The aspect of gender-related differences in occupational choices is worth a closer look: Figure 3.5 plots the fraction of FTC workers of childbearing age by occupations at a 1-digit level. The solid lines represent fractions for women, the dashed lines the fractions for men over the considered period. The fraction of male FTC workers is lowest in the occupation of *Managers* and *Technicians and Associate Professionals*. Its evolution is rather flat except for the occupations *Clerical Support Workers*, *Services and Sales Workers*, and *Elementary Occupations*, where the fractions for men show an increasing trend over the considered period. In all occupations, except for *Skilled Agricultural, Forestry and Fishery Workers*, the fraction of female FTC workers is higher than for men. As for men, fractions of female FTC workers are lowest in the occupation of *Managers* and *Technicians and Associate Professionals*. The fraction of female FTC workers shows an increasing trend in most occupations. Nevertheless, in occupations 6 to 9 fractions for women are very volatile (due their low number), which makes it difficult to see a clear trend. Nevertheless, figure 3.5 shows that the occupation and the gender are related, indicating a gender segregation to a certain extent.

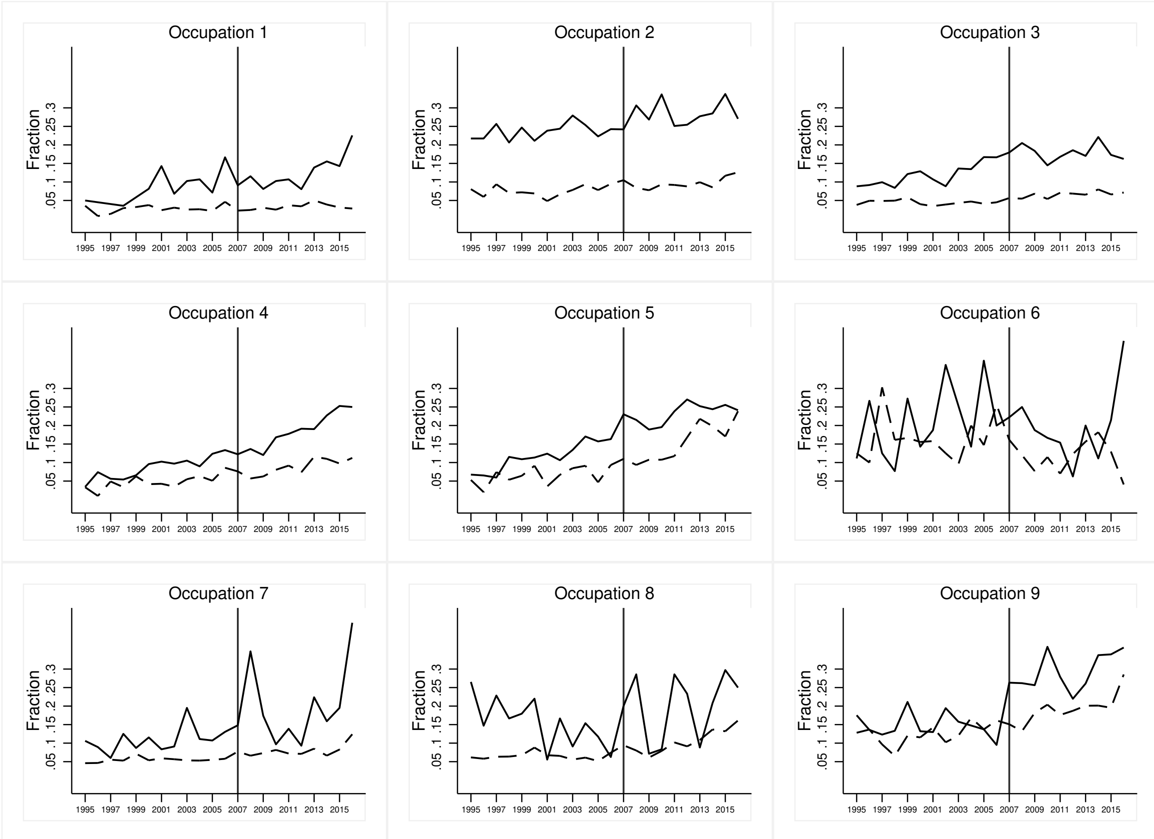
Summarising, there are slight differences within the group of women and within the group of men comparing their observables prior and after the reform. As the considered pre-reform period consists of 11 years and the post-reform period consists of 9 years, those differences are likely to be based on the sample formation. To account for different samples, I run several robustness tests in section 3.5.2, e.g. for different subgroups and by restricting the pre- and post-reform period to years directly prior and after the reform. I assume that individuals within subgroups and in a shorter considered period differ less.

In a first step I analyse whether women are (descriptively) more likely to be employed on a fixed-term basis than men after controlling for additional characteristics using a simple Linear Probability Model. Furthermore, the descriptive analysis gives a clearer picture about the determinants of FTCs. I define the regression equation as:

$$FTC_{it} = \beta_0 + \beta_1 \cdot female_i + \lambda_t + X_{it}'\gamma + u_{it} \tag{3.3}$$

where FTC_{it} is a binary variable equal to 1 if individual i is employed on a fixed-term basis in year t and zero of the individual is employed on a permanent basis, $female_{it}$ is a binary for being female, λ_t are time fixed effects, and X_{it} are additional controls which are included successively in the different specifications:

Figure 3.5: Fraction of FTC Workers by Gender and Occupation



Data Source: soep.v33.1, 2016.

Note: dashed lines are for men, solid lines for women. Occupation 1 refers to *Managers*, Occupation 2 refers to *Professionals*, Occupation 3 refers to *Technicians and Associate Professionals*, Occupation 4 refers to *Clerical Support Workers*, Occupation 5 refers to *Services and Sales Workers*, Occupation 6 refers to *Skilled Agricultural, Forestry and Fishery Workers*, Occupation 7 refers to *Craft and Related Trades Workers*, Occupation 8 refers to *Plant and Machine Operators and Assemblers*, Occupation 9 refers to *Elementary Occupations*.

Model 1 includes only the variables $female_{it}$ as control in the regression defined in Equation 3.3 and the survey year to capture time and cohort trends. Model 2 adds the age and it's squared, Model 3 the education of individuals with respect to high school, the marital status, the number of persons in the household, and the employment level of the partner. Model 4 additionally includes a binary variable for living in West Germany. Models 5 and 6 include covariates linked to the employment history, which are the full-time working experience and it's squared, the part-time working experience and it's squared, a binary variable for having been dismissed by the former employer, and a variable for the previous number of years in FTCs. In Model 7, I include job and employer characteristics like the occupation on a 1-digit level, the occupational position, the required training for the job, and the firm size. In Model 9 the number of children

is included.[28] Standard errors are clustered at the individual level. Regression results for the different specifications and for different subgroups can be found in Appendix B.2 and are purely descriptive. I analyse the probability of being employed on a fixed-term basis for the subgroups of individuals of childbearing age (young individuals, with children and without children).[29]
Considering results for the successive inclusion of control variables (Appendix B.2, Tables B.2 - B.4) yields the following main results: the indicator variable for being female shows a positive and significant correlation for the whole sample and both subgroups (with and without children) unless it is controlled for the working experience. The coefficient of the female indicator variable increases again after the inclusion of the job characteristics (firm size, occupational position, occupation, and required training). The gender shows no significant correlation for individuals with children controlling for all covariates but for the subgroup without children, the correlation is still positive and significant. Hence, there is descriptive evidence that the contract type is correlated to the gender and the magnitude of the correlation differs with job characteristics and is less pronounced for individuals with children.
Results from the simple LPM as defined in equation 3.3 and the preferred specification using all control variables described above are in table 3.3 for young individuals and for the subgroups of young individuals with and without children.[30] The effect of the gender on the probability of being employed fixed-term is positive and significant at the 10%-level (first column in table 3.3). This effect seems to be driven by young individuals without children where point estimates suggest that young women without children are associated with a higher probability of an FTC than men (1.4 percentage points). This effect is significant at the 5% level. For young individuals with children there is no significant effect of the gender detectable.
Regarding the other control variables, expectations about the direction of the correlation following from considerations in section 3.3.1 are mainly met. Only for living in West Germany and the employment level of the partner I find opposite signs of what I expected: living in West Germany has a negative correlation with the fixed-term employment probability and contract durations of partners seem to rather correspond. An increased educational attainment is associated with a lower probability of having an FTC but this effect is only significant for the highest educational level and the effect seems to be driven by young women with children. This finding

[28] For the subgroup of individuals without children, this variable is not included. The base category for this variable for the subgroup of individuals with children is *1 to 3 children*.

[29] Compared to the results from chapter 2 of this thesis, one has to keep in mind that here only individuals of childbearing age are considered.

[30] Regression results for the successive inclusion of controls as described in section 3.3.1 are in Appendix B.2, tables B.2, B.3, and B.4. The preferred specification is Model 9.

goes in line with the expectation that the probability decreases with an increasing educational attainment as it might be easier to replace lower educated workers. Being single compared to being married is associated with an increased probability as is being divorced. Single and divorced individuals bear the full responsibility for the household income and might therefore be more willing to accept any job, even an FTC. An increasing number of persons in the household is associated with a lower FTC probability though the effect is rather small and only significant at the 5%-level for young individuals with children. It might be the case that individuals with children prefer a higher job stability and are therefore less willing to accept FTCs. There is a positive correlation between the probability of being employed on a fixed-term basis and the employment level of the partner if the partner is employed on a fixed-term basis. Again this effect seems to be driven by the subgroup without children. The correlation is negative if the partner is employed on a permanent basis (compared to having no job). The significance of the effect of a permanently employed partner seems to be driven by individuals with children. The descriptive findings indicate that partners tend to have the same contract type dependent on their child-related responsibilities.

As expected from the stepping stone hypothesis and the use of FTCs as prolonged probation period, an increasing working experience (full-time and part-time) is associated with a lower probability of being employed on a fixed-term basis. This effect is significant at the 1%-level in all specifications. The reason is probably the positive signalling function of a longer working experience (see Hagen (2002)). There are negative signals to employers as well: having been dismissed by the former employer is associated with a higher FTC probability in all subgroups, significant at the 1%-level. Another negative signal seems to be the number of years in FTCs. This number has a positive effect on the probability for all subgroups, which is also significant at the 1%-level. Individuals working in larger firms seem to have a higher probability of being employed on FTCs. The probability increases with the firm size and this effect is significant in all subgroups. A reason could be a higher need to adjust the workforce in larger firms or a higher willingness to bind employees if firms are small. Not being employed in public service decreases the probability for all subgroups as well, significant at the 1%-level. Having children increases the probability. For young individuals having one to three children is associated with an increase in the probability by 2.0 percentage points.

Summarising, I find a positive correlation between the probability of being employed on a fixed-term basis and being divorced or single, having a partner who is employed on a fixed-term basis, negative employee signals (being dismissed by the last employer, a higher number of years in FTCs), working in larger firms, and of having children. I find a negative correlation with the age, having a school degree higher than high school, a permanently employed partner, living in West Germany, a higher labour market experience, and not working in public service. The coefficient of being female is positive and significant at the 10%-level for individuals (at the 5%-level for individuals without children). This could indicate that women without children are more likely to be employed on a fixed-term basis than men. But this result is purely descriptive and has no causal claim. Therefore, results from the DiD approach are given in the next section.

Table 3.3: Regression Results Basic OLS by Subgroups

Variable	Young, both	Young, with	Young, without
Dependent Variable: Binary for working in FTC/PC			
Female	0.009*	0.011	0.014**
	(0.005)	(0.009)	(0.006)
Age	-0.018**	-0.029**	-0.001
	(0.008)	(0.013)	(0.011)
Age^2	0.000**	0.001**	0.000
	(0.000)	(0.000)	(0.000)
Education w.r.t. High School:			
High School	-0.001	-0.011	0.001
	(0.006)	(0.009)	(0.009)
More than High School	-0.021**	-0.037***	-0.020
	(0.009)	(0.014)	(0.012)
Marital Status:			
Single	0.012**	0.017*	0.005
	(0.006)	(0.010)	(0.007)
Widowed	0.035	0.022	-0.075
	(0.057)	(0.064)	(0.100)
Divorced	0.024**	0.016	0.024*
	(0.011)	(0.016)	(0.014)
Separated	0.022	-0.003	0.039**
	(0.014)	(0.019)	(0.019)
Number of Persons in HH	-0.002	-0.006**	0.001
	(0.002)	(0.003)	(0.003)
Emp. Level of Partner:			
Partner employed FTC	0.016*	0.011	0.035**
	(0.008)	(0.010)	(0.017)
Partner employed PC	-0.011**	-0.011*	0.001
	(0.005)	(0.006)	(0.013)
No Partner	-0.003	0.013	0.006
	(0.007)	(0.014)	(0.013)
West Germany	-0.025***	-0.030***	-0.018***
	(0.005)	(0.007)	(0.006)
Full-Time Employment Experience	-0.052***	-0.038***	-0.065***
	(0.002)	(0.003)	(0.003)
Full-Time Employment Experience^2	0.002***	0.002***	0.003***
	(0.000)	(0.000)	(0.000)
Part-Time Employment Experience	-0.014***	-0.021***	-0.009**
	(0.003)	(0.004)	(0.005)
Part-Time Employment Experience^2	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.001)
Indicator for Dismissal by former Employer	0.216***	0.216***	0.209***
	(0.016)	(0.024)	(0.021)
Number of previous FTCs	0.063***	0.054***	0.071***
	(0.003)	(0.005)	(0.005)
Firm Size:			
5 to 20 Employees	0.032***	0.037***	0.029***
	(0.007)	(0.010)	(0.009)
More than 20, Less than 200 Employees	0.054***	0.046***	0.061***
	(0.007)	(0.009)	(0.009)
More than 200 Employees	0.059***	0.061***	0.058***
	(0.006)	(0.009)	(0.009)
Not working in Public Service	-0.091***	-0.081***	-0.097***
	(0.007)	(0.010)	(0.008)
Number of Children:			
1-3 Children	0.020***		
	(0.006)		
4 or more Children	-0.019	-0.019	
	(0.020)	(0.020)	
Constant	0.671***	0.842***	0.439***
	(0.120)	(0.198)	(0.162)
Survey Year	Yes	Yes	Yes
Occupational Position	Yes	Yes	Yes
Occupation	Yes	Yes	Yes
Required Training	Yes	Yes	Yes
Adj. R-Square	0.162	0.143	0.183
Number of Obs.	37,106	16,145	20,961
F-Test (p-value)	0.00	0.00	0.00

Note: Regressions are estimated with OLS. In the different columns regression results from the preferred specification for different subgroups are represented. Results for the different specifications can be found in the Appendix. The base category for the educational attainment is *Less than High School*, for the marital status *Married*, for the employment level of the partner *Partner not employed*, for the firm size *Less than 5*, and for the number of children *No children*. Standard errors appear in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. *F-Test* (p-value) denotes the p-value associated with an F-test of joint significance of the included controls. Standard errors are clustered at the indivial level. Data Source: soep.v33.1, 2016.

3.4 Results

3.4.1 Results Reform 2007 - DiD

Regression results from the difference-in-differences model as defined in equation 3.1 for the different subgroups are in table 3.4.[31] Control variables are the same as described in the last section for the preferred specification (Model 9 for all young individuals, Model 8 for young individuals without children, as described in section 3.3.2). Standard errors are clustered at the individual level.

For the subgroup of individuals of childbearing age, the coefficient of the interaction term as defined in equation 3.1, β_3, is significant at the 10%-level and positive. The probability of being employed on a fixed-term basis increases for young women after the reform by 1.5 percentage points (roughly 12%). As the coefficient of $female_{it}$, β_1, is not significant, there is no evidence for a mean difference in the probability between young men and women prior the reform.

The question is whether the significant result for the effect of the interaction term is driven by perceptions of employers about the probability that a woman becomes pregnant. It could be that employers perceive the probability of a pregnancy as higher if women have no children but are of childbearing age. Then the reform should have an effect on women without children but not on women with children. Indeed, this seems to be the case as the coefficient of the interaction is significant for young individuals without children but it is not significant for the subgroup with children (table 3.4, columns 2 and 3). In table 3.4, column 3 for the subgroup without children, the coefficient of the interaction term is positive and significant at the 5%-level. This indicates that the reform had an effect on women of childbearing age without children but not on those with children. The point estimate suggests an increase of the probability for young women without children of 2.3 percentage points (roughly 18%). Considering only married women without children for which the "risk" of pregnancy should be perceived as even higher, the coefficient of the interaction term indicates an increase in the probability for women after the reform of 3.9 percentage points, significant at the 10%-level. My results indicate that women seem to be disadvantaged in terms of their contract type. This disadvantage cannot be explained by child-related absences and therefore a lower labour market experience as the effect is driven by young women without children (potential mothers) and the labour market experience is controlled for.

[31] Results for the successive inclusion of controls are given in Appendix B.3, table B.5 for individuals of childbearing age, in Appendix B.3, table B.6 for individuals of childbearing age with children, and in Appendix B.3, table B.7 for individuals without children.

I find that the disadvantage is more pronounced for potential mothers and even increases for young and married women without children which form the group with the highest perceived “risk” of pregnancy.

The question remains whether the disadvantage of a higher probability of being employed on a fixed-term basis is linked to the childbearing age or the gender generally. To figure out the difference in the probability not only compared to men but also to older women, I apply a DDD approach following equation 3.2.

Table 3.4: Regression Results DD by Subgroups

Variable	Young, both	Young, with	Young, without	Married Young, without
Dependent Variable: Binary for working in FTC/PC				
Female	0.003	0.010	0.005	-0.010
	(0.006)	(0.010)	(0.007)	(0.013)
Reform 2007	0.015***	0.029***	0.001	-0.016
	(0.005)	(0.007)	(0.007)	(0.015)
Reform 2007 × Female	0.015*	0.005	0.023**	0.039*
	(0.008)	(0.013)	(0.011)	(0.022)
Age	-0.018**	-0.029**	-0.002	-0.012
	(0.008)	(0.013)	(0.011)	(0.030)
Age^2	0.000**	0.001**	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Education w.r.t. High School:				
High School	-0.001	-0.011	0.002	0.002
	(0.006)	(0.009)	(0.009)	(0.019)
More than High School	-0.021**	-0.036***	-0.018	-0.033
	(0.009)	(0.014)	(0.012)	(0.024)
Marital Status:				
Single	0.013**	0.016*	0.007	
	(0.006)	(0.010)	(0.007)	
Widowed	0.035	0.022	-0.081	
	(0.057)	(0.064)	(0.104)	
Divorced	0.024**	0.016	0.024*	
	(0.011)	(0.016)	(0.014)	
Separated	0.022	-0.002	0.038*	
	(0.014)	(0.020)	(0.019)	
Number of Persons in HH	-0.002	-0.006**	0.001	0.012
	(0.002)	(0.003)	(0.003)	(0.012)
Emp. Level of Partner:				
Partner employed FTC	0.017**	0.010	0.037**	0.019
	(0.008)	(0.010)	(0.017)	(0.025)
Partner employed PC	-0.011**	-0.012*	0.001	0.009
	(0.005)	(0.006)	(0.013)	(0.020)
No Partner	-0.004	0.012	0.005	0.064
	(0.007)	(0.014)	(0.013)	(0.095)
West Germany	-0.025***	-0.031***	-0.018***	0.001
	(0.005)	(0.007)	(0.006)	(0.016)
Full-Time Employment Experience	-0.051***	-0.038***	-0.065***	-0.042***
	(0.002)	(0.003)	(0.003)	(0.006)
Full-Time Employment $Experience^2$	0.002***	0.001***	0.003***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Part-Time Employment Experience	-0.014***	-0.021***	-0.009**	-0.001
	(0.003)	(0.004)	(0.005)	(0.008)
Part-Time Employment $Experience^2$	-0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.001)	(0.001)
Indicator for Dismissal by former Employer	0.216***	0.216***	0.209***	0.265***
	(0.016)	(0.024)	(0.021)	(0.053)
Number of previous FTCs	0.063***	0.052***	0.072***	0.060***
	(0.003)	(0.005)	(0.005)	(0.010)
Firm Size:				
5 to 20 Employees	0.032***	0.036***	0.028***	0.008
	(0.007)	(0.010)	(0.009)	(0.020)
More than 20, Less than 200 Employees	0.053***	0.045***	0.060***	0.025
	(0.007)	(0.009)	(0.009)	(0.021)
More than 200 Employees	0.058***	0.060***	0.057***	0.033
	(0.006)	(0.009)	(0.009)	(0.020)
Public Service: No	-0.091***	-0.082***	-0.096***	-0.079***
	(0.007)	(0.010)	(0.008)	(0.016)
Number of Children:				
1-3 Children	0.020***			
	(0.006)			
4 or more Children	-0.019	-0.020		
	(0.020)	(0.020)		
Constant	0.682***	0.841***	0.447***	0.609
	(0.120)	(0.199)	(0.162)	(0.436)
Occupational Position	Yes	Yes	Yes	Yes
Occupation	Yes	Yes	Yes	Yes
Required Training	Yes	Yes	Yes	Yes
Adj. R-Square	0.162	0.143	0.183	0.152
Number of Obs.	37,106	16,145	20,961	3,570
F-Test (p-value)	0.00	0.00	0.00	0.00

Note: Regressions are estimated with OLS. In the different columns regression results from the preferred specification for different subgroups are represented. Results for the different specifications can be found in the Appendix. The base category for the educational attainment is *Less than High School*, for the marital status *Married*, for the employment level of the partner *Partner not employed*, for the firm size *Less than 5*, and for the number of Children *No Children*. Standard errors appear in parentheses and are clustered at the individual level. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. *F*-Test (p-value) denotes the p-value associated with an *F*-Test of joint significance of the included controls. Data Source: soep.v33.1, 2016.

3.4.2 Results Reform 2007 - DDD

Regression results of the DDD approach defined in equation 3.2 and from the preferred specification (Model 9 for all individuals, Model 8 for individuals without children) for the different subgroups are in table 3.5, where different columns refer to the groups of all individuals, non-parents, and parents.[32] The regression coefficient of interest as defined in equation 3.2, $\hat{\delta}_7$, is positive in the whole sample and in the subgroup without children, indicating that women of childbearing age have a higher probability to be employed on a fixed-term basis than men and older women. Considering all individuals (table 3.5, column 1), the effect is significant at the 10%-level and indicates an increase of the FTC probability of 1.6 percentage points. Again, like in the DiD analysis, this effect seems to be driven by potential mothers. The effect for individuals with children is very small and not significant. For individuals without children the point estimate suggests an increase of 3.1 percentage points, which is significant at the 5%-level.
The coefficient of being female, $\hat{\delta}_1$ in equation 3.2, is very small and only significant in the subgroup without children. The point estimate suggests that the probability for old women prior the reform was 0.7 percentage points lower than for old men without children. The probability of having an FTC seems to have decreased after the reform for older men without children. For this subgroup, the point estimate suggests a significant decrease of 0.9 percentage points. Considering the probability decreasing effect of the age, the sign of the coefficient of the childbearing age, $\hat{\delta}_3$ in equation 3.2, is surprising. It is negative and significant which indicates that young men prior the reform had a lower probability than older men in all subgroups. The coefficient of the interaction term of $female_{it} \times cbage_{it}$, $\hat{\delta}_5$ in equation 3.2, is positive but not significant. Hence, there is no reliable evidence that the gender gap was different for young and old individuals prior the reform. Looking at the gender-related reform effect for old individuals, the coefficient of the interaction term of $female_{it} \times reform_{it}$, $\hat{\delta}_4$ in equation 3.2, indicates that the probability of FTCs increased for old women as well (by 0.7 percentage points for all individuals and 1.2 percentage points for the subgroup with children).[33] The positive and highly significant result for the coefficient of the interaction term of $reform_{it} \times cbage_{it}$, $\hat{\delta}_6$ in

[32] Results for the DDD approach and the successive inclusion of controls are presented in table B.8, Appendix B.4. The regression coefficient of interest as defined in equation 3.2, $\hat{\delta}_7$, is positive after controlling for the age and it's squared (Model 2). From the specification in Model 6 onwards, it is positive and significant at the 10%-level.

[33] In an analysis not presented here, I apply the DiD approach presented in section 3.3.1 as well for the subgroup of older individuals and find a significant coefficient of the interaction term, $\hat{\beta}_3$ in equation 3.1. But as the parallel paths assumption is not fulfilled for the older age group, this result is not reliable. Results are obtainable by the author upon request.

equation 3.2, indicates that the probability increasing effect of the reform was higher for young than for old men. For young men without children, the probability increased by 2.4 percentage points and by 3.2 percentage points for young men with children compared to older men. The difference in the stated effects could indicate that the probability increasing effect for young men might not be solely explained by the general increase in the use of FTCs but might be related to childcare responsibilities. This aspect is not further considered here but stays for further research. The application of the DDD approach shows that there is evidence that women of childbearing age are disadvantaged compared to men and older women in terms of their contract duration, which is more pronounced in the risk group of potential mothers.

3.5 Robustness

3.5.1 Parallel Paths and Placebo Tests

Besides the fertility increasing effect of the reform, two major assumptions should hold true for the reliability of the results from the DiD analyses: First, the parallel paths assumption has to be fulfilled, i.e. that the probability of being employed fixed-term has to follow the same trend for the treatment and control group prior the reform. Second, the reform in 2007 has a significant effect on the probability of being employed on a fixed-term basis and there should be no significant effects in years where there was no reform. I test this using placebo reforms. In the analyses using the DiD approach in section 3.4.1 the effect of the interaction term of $Female \times Reform2007$ was significant for all young individuals and young individuals without children which is why I concentrate on these two groups in the following.

Parallel Paths

The main assumption for a DiD approach is the assumption of parallel paths. The visual inspection of figures 3.2 and 3.3 suggests that the evolution of fractions of FTC workers prior to the reform is parallel for men and women, which is more apparent for individuals of childbearing age. Following the considerations of Autor (2003), I analyse the assumption formally by including leads and lags for the years before and after the reform in 2007 in the regression as well as their interaction with the treatment variable. The regression equation is then defined as:

$$FTC_{it} = \beta_0 + \beta_1 \cdot female_{it} + \lambda_t + \beta_p \sum_{p=1995}^{q=2005} d_p \times female_{it} + \beta_a \sum_{a=2007}^{q=2016} d_a \times female_{it} + X_{it}'\gamma + \varepsilon_{it} \tag{3.4}$$

λ_t are year fixed effects, d_p are dummies for the respective year ranging from 1995 to 2005, and d_a are dummies for the years 2007 to 2016. X_{ist}' contains covariates of the preferred specification are used. If the parallel paths assumption is fulfilled and the reform had an effect on the treatment group, coefficients for the interaction prior the reform, β_{1995} to β_{2005} should be zero, whereas coefficients after the reform β_{2007} to β_{2016} should be different from zero. Table 3.6 shows the results for all young individuals and table 3.7 for the subgroup of young individuals without children. The coefficients of the interaction terms prior the reform are rather small and mainly not significant. The F-test shows that coefficients prior the reform are jointly insignificant, whereas the coefficients after the reform are jointly significant. This suggests that the parallel paths assumption is likely to be fulfilled using young men (without children) as control for young women (without children).

Placebo Tests

If the results of a significant effect of the reform are robust, there should be no significant effect of "placebo" reforms in other years. To test this, I regress equation 3.1 again using several reform dummies for $reform_{it}$. Those indicate reforms in 1997 to 2006. The follow up periods are restricted until 2006 to avoid biases from the reform in 2007, e.g. for the placebo reform in 2006, there is one post-reform period (2006); for the placebo reform in 2005 there are two post-reform periods (2005, 2006) etc. In table 3.8, I present results from these regressions for the subgroup of young individuals and in table 3.9 for young individuals without children. The last column in both tables shows the effect of the true reform in 2007. For both groups the coefficient of the interaction term is positive for the placebo reforms in 1997 to 2001 and turns negative for the following placebo reforms. A positive (negative) coefficient of the interaction term indicates that women after the reform have a higher (lower) probability of being employed on a fixed-term basis than men. Coefficients of the placebo reforms are very small in absolute terms and none of the interaction coefficients is significant. Therefore, there is no evidence that one of the placebo reforms had a significant effect on the probability of being employed on a fixed-term basis.

Both, the test for the parallel paths assumption and the test of the placebo reforms indicate that results for the subgroup of young individuals are reliable. Hence, these tests strengthen my major result: women of childbearing age, for which the risk of a pregnancy related downtime is higher, are more likely to be employed on a fixed-term basis.

3.5.2 Robustness Tests

Different periods

Results of the descriptive analysis indicated that the sample formation differs slightly prior and after the reform. As the number of considered pre- and post-reform years is high, I estimate equation 3.1 again using only one pre-reform year (2006), the reform year (2007) and one post-reform year (2008) to test whether results are robust. By restricting the number of periods in this way, the pre- and post sample formation should be rather equal. Table 3.10 shows regression results for the subgroups of young individuals. Thereby, control variables from specification "Model 9" are used. The coefficient of the interaction term, β_3 (eq. 3.1), is positive and significant at the 10%-level for young individuals. Therefore, the probability increasing effect of the reform is still detectable if I use a lower number of pre- and post reform periods and results should not stem from sample formation.

Different definition of the childbearing age

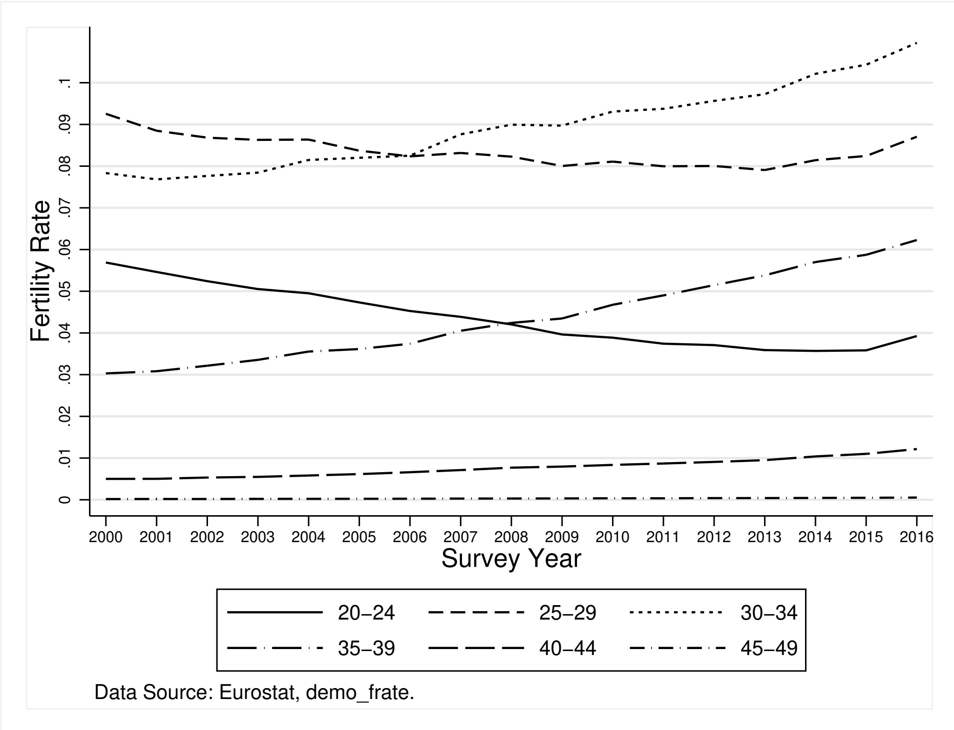
Following Puhani and Sonderhof (2011), the childbearing age was defined as 20-35. To test whether the significant effect remains with different specifications of the childbearing age, I run the regressions of the DiD approach defined in equation 3.1 again, defining the childbearing age as 20-40. In figure 3.6, fertility rates for different age groups for the years 2000-2016 are displayed.[34] Fertility rates of the two youngest age groups (20-24 and 25-29) decreased whereas fertility rates of the age groups 30-34 and 35-39 increased over the displayed period. Fertility rates in the age group of 30-34 are highest from 2006 onwards. Still the fertility rates in the older age groups 40-44 and 45-49 are very low compared to the other age groups, which is why I define the childbearing age for the robustness test as 20-40.

Results from the regression with the new definition of the childbearing age are displayed in table 3.11. The coefficient of the interaction term using all individuals in the childbearing age is still of the same magnitude but the significance increased to a 5%-level. The coefficient of the

[34] Based on Eurostat data (demo_frate, extracted on 18.12.2019), data for the years 1995-1999 not available. Eurostat (2019).

interaction term for individuals with children increased slightly but still is not significant. For individuals without children, the coefficient of the interaction term decreases to 1.9 percentage points but is still significant at the 5%-level. For married individuals without children, the coefficient of interest also decreases slightly (3.6 percentage points) but significance increases to a 5%-level. Hence, even with a extended definition of the childbearing age, there is still a significant positive effect which indicates that women after the reform are more likely to be employed on a fixed-term basis than men in the same age group. The slightly lower magnitude of the effect could reflect the lower fertility rate in the age group 36-40.

Figure 3.6: Fertility Rates by Age Group



3.5.3 Subgroup Analysis

Subgroups by income classes

The major change that the reform in 2007 implemented was the introduction of different parental benefits for different income levels (see section 3.2). The inciting effect of the reform should therefore vary with income levels. As results from literature have shown, the wage of fixed-term contract workers is lower than of their permanently employed counterparts.[35] Therefore, I consider the wage to be endogenous and do not control for it in my regressions. To account for the

[35]See e.g. Booth et al. (2002), la Rica (2004), Mertens et al. (2007), Hagen (2002), and Gebel (2009).

aspect of differing inciting effects by wages and to analyse whether the probability increasing effect is present in different income subgroups, I apply the DiD approach defined in equation 3.1 to the following income-subgroups: those who are eligible for benefits higher than 100%, 67-99%, 65-66.9%, and less than 65%.[36] Those who would receive 100% or more have an average pre-birth income of 300 Euro. Before the reform, parental benefits were 300 Euro for two years so that this group should not be additionally incited by the reform (see as well Kluve and Schmitz (2014)). Regression results are displayed in table 3.12 for all young individuals and in table 3.13 for young individuals without children.[37]

The effect of an increased FTC probability after the reform seems to be driven by women in the second lowest income group who have no children. First, considering all individuals, the coefficient of the interaction term is positive for the first three income classes and negative for the highest income class. But the effect is for any income subgroups significant. Second, considering the subgroup of potential mothers changes results. The results from section 3.4.1 show, the effect of the reform was driven by this subgroup. There is still no significant effect detectable for the lowest income class as expected. There is no significant effect for the income class who is eligible for 65-66.9% either but for the second income class (eligible for benefits of 67-99%) the coefficient of the interaction term is positive and significant at the 5%-level. The point estimate suggests that the probability of being employed on a fixed-term basis increases for young women without children with an income of 361-1000 Euro by 3.8 percentage points. On the contrary the effect is negative and significant at the 1%-level for the highest income group (eligible for less than 65%). The point estimate suggests that the probability for this subgroup decreases by 14.9 percentage points. A potential reason for this negative effect could be that individuals in this income group cannot be easily replaced and therefore employers are more likely to offer permanent contracts. Still, the number of observations in this subgroup is rather low (419) compared to the number of observations in the second income class (9640). Even if there is a true negative effect on the fixed-term probability, i.e. no disadvantage for these women, only a comparably low number of women benefits (less than 2% in the highest income class compared to nearly 45% in the second income class). Hence, there are more women who

[36] Different groups are displayed in the different columns of the associated tables.

[37] For the regressions, I used a reduced model excluding widowed individuals because of their very low number in the subgroups. Furthermore, I do not control for the occupational position and the required training for the job, as again observational numbers in some categories of those variables were very low due to their dependence on the income level.

face a disadvantage than women who benefit.

New Hires

There is evidence that the effect exists for restricting the sample to only newly hired employees. One major concern about the analysis could be that all workers are considered and not only those with "new" contracts. Permanent contracts are supposed to be of a longer duration than fixed-term contracts and employers do not have to decide about the contract type again when individuals are already hired permanently. As discussed in section 3.3.1, there are two main reasons why I use the stock of all employed individuals and not only those with new contracts for which the decision about the contract type was made in the respective survey year: the low number of new hires (for which the model would be too complex) and the potential selection.

The use of the stock of all employment relationships does not contradict the argumentation: By using the stock of all employment relationships, I find an increased probability for young women (especially potential mothers) to be employed on a fixed term basis. If one would now assume that employers do not face the decision of which contract type to use when women are already employed on a permanent basis, the effect should be smaller. If I use all employed individuals in the respective age groups, then the effect found is a lower bound of the effect for new hires and the disadvantage for women should be even higher.

To analyse this aspect, I apply a DiD approach for the subgroup of new hires with a reduced model.[38] There is an increase in the number of new hires after the reform (section 3.3.1, table 3.1). One could argue that the higher increase of new hires of women could be caused by their increased labour market attachment/participation (see e.g. Kluve and Tamm (2013)). To refute or at least mitigate this argument, table 3.14 shows the regression results of the DiD approach for the subgroups of new hires.[39] The coefficient of interest (β_3 from equation 3.1) increases for all individuals from 0.015 to 0.082 (standard error = 0.045; corresponds to around 25%) and for individuals without children from 0.023 to 0.134 (standard error = 0.06; corresponds to around 39%) while the significance levels stay the same. Hence, there is evidence that the effect of the reform found in this chapter exists considering only new hires. As the number of observations in the subgroup is relatively low and a rich set of control variables is used, the coefficients should be interpreted with care. Furthermore, this subgroup of newly hired individuals only includes

[38] *New contract* or *new hire* means that the individual was hired in the respective survey year.

[39] The variable containing information on the occupational position used in the regressions on the full sample above had to be excluded as control due to the low number of observations in some of the categories.

individuals with a contract duration of up to one year such the effect found only holds for these workers and results cannot be extrapolated to the group of all FTC workers.

3.6 Discussion and Conclusion

Gender differences in labour market outcomes such as wage or promotion probabilities are well analysed in the literature for many countries while there is much less evidence on the contract type. It has been shown that there are gender-related differences concerning contract duration (e.g. Petrongolo (2004), Berton and Garibaldi (2012), Dalla Chiara et al. (2014), and Fernández-Kranz and Rodríguez-Planas (2011)) and authors suggest that this difference stems from employers anticipating the risk of a child-related leave. Nevertheless, causal evidence supporting this argument was missing for Germany. I fill this gap by analysing whether the risk group of women of childbearing age is disadvantaged in terms of their contract type.

Descriptive findings indicating that women are more likely to be employed on a fixed-term basis after controlling for various personal and job characteristics are confirmed by my analysis. My descriptive results provide a first hint that this effect stems from young women without children: potential mothers. To find causal evidence for this, I apply a DiD approach. With a reform in 2007 that increased parental benefits dependent on the pre-birth income considerably for a large fraction of women, it was intended to increase fertility rates and to strengthen the labour market attachment of women. As findings from literature show, intentions from the reform were met (e.g. Stichnoth (2019), Raute (2019), Bergemann and Riphahn (2011), Kluve and Tamm (2013), and Kluve and Schmitz (2014)). My results additionally show a negative side effect of this reform: the increase in the gender gap in the FTC probability. I find that young women after the reform are significantly more likely to be employed fixed-term than men, a finding that cannot be explained by a different working experience or child-related engagements. This becomes clear as the probability increasing effect is driven by young women without children and is even larger in the subgroup of married and childless women. To analyse whether this effect is truly age-group related or just gender-related, I apply a DDD approach to compare effects for young women to effects for men and older women. Results from this confirm the argument of a pregnancy-risk related link to the contract type: potential mothers after the reform are more likely to be employed fixed-term than men and older women. As it can be argued that incentives from the reform and therefore the perceived risk of a leave can differ by income levels, I analysed effects for income subgroups. Results show that the the effect that women are more likely to have an FTC is apparent for the second lowest income group of potential mothers (eligible for 67-99% of average pre-birth income).

The formal analysis of the parallel paths assumptions suggest that there is no evidence for a violation of it and placebo-reforms show no significant effects. Restricting the analysis to a shorter pre- and post reform period shows that results are not likely to stem from a different pre- and post reform sample formation. The extension of the definition of the childbearing age and therefore accounting for an increased age of first-birth over the considered period, gives comparable results.

Some aspects of sample formation are worth mentioning at this point: a potential self-selection into motherhood related to the reform and a potential preference of employers for certain types of replacing workers. The presented analysis does not account for a delay of motherhood to the post-reform period. Tamm (2013) finds that roughly 8% of births were postponed to January 2007 (Tamm (2013), p. 598). This would provide evidence for a self-selection into the post-reform group of parents. As I argue that differences exist for non-parents, this postponement should not change my findings.

In the analysis, I do not account for replacing workers for reasons of data availability. If a female employee has to be replaced because of parental leave, the employer might have a certain preference for the replacing worker being female. If you hire a replacing employee, this employment relationship will usually be limited in time (FTC with factual reason). Following this logic: Are my results driven by replacing workers? Stichnoth (2019) finds an increase in the number of births 5 years after the reform of 4%. Comparing this fertility increase to my results, my findings are not likely to be driven solely by replacing workers as I find a higher increase in the probability to be fixed-term employed (12%). Considering the problem of replacing workers, my results could be an upper bound.

My analyses show that potential mothers are not equally well off in terms of their contract duration linked to their general ability to have children. How could the gender gap be narrowed? The policy implication following my results could be to set an increased incentive for men to take longer parental leave. Although the months of the parental leave can be freely divided between mothers and fathers, Kluve and Tamm (2013) find that the majority of fathers takes only two months. As two months is a comparably short period, employers might not feel the need for a costly replacement for this time and might perceive the resulting expense as lower than for women. Increasing incentives for men to take more than two months of parental leave could adjust the differences in gender-related perceptions concerning the length of absences. Still one has to keep in mind that the decision about who takes the longer parental leave depends on the income: the partner with the lower income is probably more likely to take longer parental leave. Therefore, incentives for fathers should take this consideration into account. Results from my DDD analysis provide evidence that the reform also had an effect for young men compared to older men that is linked to their child-care responsibilities. Further research could address this by linking these findings to the considerations of an increased incentive for longer absences of fathers.

Table 3.5: Regression Results DDD for Different Subgroups

Variable	All	Without Children	With Children
Dependent Variable: Binary for working in FTC/PC			
Female	-0.002	-0.007*	0.008*
	(0.003)	(0.004)	(0.005)
Reform 2007	-0.006**	-0.009**	-0.002
	(0.002)	(0.004)	(0.003)
Childbearing Age	-0.045***	-0.066***	-0.031***
	(0.004)	(0.007)	(0.006)
Female × Childbearing Age	0.008	0.008	0.010
	(0.005)	(0.007)	(0.008)
Female × Reform 2007	0.007*	-0.001	0.012**
	(0.004)	(0.005)	(0.006)
Reform 2007 × Childbearing Age	0.028***	0.024***	0.032***
	(0.005)	(0.008)	(0.007)
Female × Reform 2007 × Childbearing Age	0.016*	0.031**	0.000
	(0.009)	(0.012)	(0.013)
Age	-0.014***	-0.013***	-0.013***
	(0.002)	(0.002)	(0.003)
Age^2	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Education w.r.t. High School:			
High School	0.008**	0.013***	0.004
	(0.003)	(0.005)	(0.005)
More than High School	0.003	0.012**	-0.003
	(0.004)	(0.006)	(0.006)
Marital Status:			
Single	0.014***	0.005	0.025***
	(0.004)	(0.005)	(0.006)
Widowed	-0.009	-0.000	-0.026*
	(0.009)	(0.010)	(0.015)
Divorced	0.015***	0.019***	0.002
	(0.004)	(0.005)	(0.007)
Separated	0.013**	0.014*	-0.001
	(0.006)	(0.008)	(0.009)
Number of Persons in HH	-0.000	0.000	-0.000
	(0.001)	(0.001)	(0.001)
Emp. Level of Partner:			
Partner employed FTC	0.019***	0.019***	0.017***
	(0.004)	(0.007)	(0.005)
Partner employed PC	-0.012***	-0.016***	-0.011***
	(0.002)	(0.005)	(0.003)
No Partner	0.004	-0.004	0.019***
	(0.004)	(0.006)	(0.007)
West Germany	-0.022***	-0.023***	-0.019***
	(0.002)	(0.003)	(0.003)
Full-Time Employment Experience	-0.013***	-0.016***	-0.012***
	(0.001)	(0.001)	(0.001)
Full-Time Employment $Experience^2$	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Part-Time Employment Experience	-0.008***	-0.005***	-0.012***
	(0.001)	(0.001)	(0.001)
Part-Time Employment $Experience^2$	0.000**	-0.000	0.000***
	(0.000)	(0.000)	(0.000)
Indicator for Dismissal by former Employer	0.220***	0.219***	0.219***
	(0.011)	(0.015)	(0.015)
Number of previous FTCs	0.054***	0.055***	0.055***
	(0.002)	(0.003)	(0.003)
Firm Size:			
5 to 20 Employees	0.019***	0.015***	0.021***
	(0.004)	(0.006)	(0.005)
More than 20, Less than 200 Employees	0.030***	0.031***	0.028***
	(0.004)	(0.005)	(0.005)
More than 200 Employees	0.029***	0.027***	0.030***
	(0.004)	(0.005)	(0.005)
Public Service: No	-0.041***	-0.043***	-0.040***
	(0.003)	(0.004)	(0.004)
Number of Children:			
1-3 Children	0.017***		
	(0.003)		
4 or more Children	0.021***		0.006
	(0.008)		(0.008)
Constant	0.376***	0.387***	0.525***
	(0.037)	(0.051)	(0.058)
Occupational Position	Yes	Yes	Yes
Occupation	Yes	Yes	Yes
Required training	Yes	Yes	Yes
Adj. R-Square	0.126	0.135	0.121
Number of Obs.	121,109	58,583	62,526
F-Test (p-value)	0.00	0.00	0.00

Note: Regressions are estimated with OLS. In the different columns regression results from the preferred specification for different subgroups are presented. The base category for the educational attainment is *Less than High School*, for the marital status *Married*, for the employment level of the partner *Partner not employed*, for the firm size *Less than 5*, and for the number of Children *No Children*.Standard errors appear in parentheses and are clustered at the individual level. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. F-Test (p-value) denotes the p-value associated with an F-Test of joint significance of the included controls. Data Source: soep.v33.1, 2016.

Table 3.6: Test for Parallel Paths - Young Individuals

Variable	
1995 × Female	0.007
	(0.020)
1996 × Female	0.014
	(0.020)
1997 × Female	0.011
	(0.020)
1998 × Female	0.015
	(0.020)
1999 × Female	0.014
	(0.020)
2000 × Female	0.035*
	(0.019)
2001 × Female	0.035*
	(0.019)
2002 × Female	0.020
	(0.019)
2003 × Female	0.024
	(0.020)
2004 × Female	0.010
	(0.020)
2005 × Female	0.033*
	(0.019)
2007 × Female	-0.003
	(0.021)
2008 × Female	0.086***
	(0.023)
2009 × Female	0.024
	(0.023)
2010 × Female	0.035
	(0.023)
2011 × Female	0.046**
	(0.023)
2012 × Female	0.049**
	(0.024)
2013 × Female	0.025
	(0.024)
2014 × Female	0.040
	(0.026)
2015 × Female	0.027
	(0.025)
2016 × Female	0.009
	(0.026)
Adj. R-Square	0.162
Number of Obs.	37,106
***F*-Test (p-value) pre**	**0.61**
***F*-Test (p-value) post**	**0.01**

Note: Standard errors appear in parentheses and are clustered at the individual level. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Additional Controls like in preferred specification. F-Test pre (p-value) denotes the p-value associated with an F-Test of joint significance of the interactions before the reform for the years 1995-2005, F-Test post for the years after the reform 2007-2016. The base year is 2006. Data Source: soep.v33.1, 2016.

Table 3.7: Test for Parallel Paths - Young Individuals Without Children

Variable	
1995 × Female	-0.001
	(0.025)
1996 × Female	-0.007
	(0.025)
1997 × Female	0.006
	(0.025)
1998 × Female	0.010
	(0.025)
1999 × Female	0.000
	(0.026)
2000 × Female	0.038
	(0.025)
2001 × Female	0.029
	(0.024)
2002 × Female	0.007
	(0.024)
2003 × Female	0.016
	(0.026)
2004 × Female	0.011
	(0.026)
2005 × Female	0.022
	(0.025)
2007 × Female	0.001
	(0.026)
2008 × Female	0.080***
	(0.029)
2009 × Female	0.008
	(0.029)
2010 × Female	0.034
	(0.031)
2011 × Female	0.042
	(0.030)
2012 × Female	0.061*
	(0.031)
2013 × Female	0.039
	(0.032)
2014 × Female	0.057*
	(0.033)
2015 × Female	0.032
	(0.031)
2016 × Female	-0.004
	(0.034)
Adj. R-Square	0.184
Number of Obs.	20,961
***F*-Test (p-value) pre**	**0.75**
***F*-Test (p-value) post**	**0.07**

Note: Standard errors appear in parentheses and are clustered at the individual level. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Additional Controls like in preferred specification. F-Test pre (p-value) denotes the p-value associated with an F-Test of joint significance of the interactions before the reform for the years 1995-2005, F-Test post for the years after the reform 2007-2016. The base year is 2006. Data Source: soep.v33.1, 2016.

Table 3.8: Placebo Tests DD - Subgroup Young Individuals

Variable	Placebo 1997	Placebo 1998	Placebo 1999	Placebo 2000	Placebo 2001	Placebo 2002	Placebo 2003	Placebo 2004	Placebo 2005	Placebo 2006	Reform 2007
Female	-0.002	-0.002	-0.001	-0.001	0.004	0.006	0.006	0.006	0.006	0.007	0.003
	(0.010)	(0.009)	(0.008)	(0.008)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Reform 1997	0.001										
	(0.008)										
Reform 1997 × Female	0.009										
	(0.010)										
Reform 1998		-0.001									
		(0.008)									
Reform 1998 × Female		0.010									
		(0.009)									
Reform 1999			-0.008								
			(0.008)								
Reform 1999 × Female			0.010								
			(0.009)								
Reform 2000				-0.001							
				(0.009)							
Reform 2000 × Female				0.011							
				(0.009)							
Reform 2001					-0.019**						
					(0.008)						
Reform 2001 × Female					0.004						
					(0.009)						
Reform 2002						-0.002					
						(0.008)					
Reform 2002 × Female						-0.002					
						(0.009)					
Reform 2003							0.019**				
							(0.009)				
Reform 2003 × Female							-0.003				
							(0.010)				
Reform 2004								0.010			
								(0.009)			
Reform 2004 × Female								-0.006			
								(0.011)			
Reform 2005									-0.006		
									(0.010)		
Reform 2005 × Female									-0.002		
									(0.013)		
Reform 2006										0.019	
										(0.012)	
Reform 2006 × Female										-0.020	
										(0.016)	
Reform 2007											0.015***
											(0.005)
Reform 2007 × Female											**0.015***
											(0.008)
Additional Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-Square	0.151	0.151	0.151	0.151	0.151	0.151	0.151	0.151	0.151	0.151	0.162
Number of Obs.	23,303	23,303	23,303	23,303	23,303	23,303	23,303	23,303	23,303	23,303	37,106
F-Test (p-value)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Note: Regressions are estimated with OLS. The different columns represent Placebo tests for the years 1997-2006. Additional controls are as in the preferred specification. Standard errors appear in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. F-Test (p-value) denotes the p-value associated with an F-Test of joint significance of the included controls. Standard errors are clustered at the indivial level. Data Source: soep.v33.1, 2016.

Table 3.9: Placebo Tests DD - Subgroup Young Individuals Without Children

Variable	Placebo 1997	Placebo 1998	Placebo 1999	Placebo 2000	Placebo 2001	Placebo 2002	Placebo 2003	Placebo 2004	Placebo 2005	Placebo 2006	Reform 2007
Female	-0.009	-0.007	-0.005	-0.005	0.002	0.005	0.004	0.004	0.004	0.005	0.010
	(0.013)	(0.011)	(0.010)	(0.010)	(0.009)	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)
Reform 1997	0.004										
	(0.012)										
Reform 1997 × Female	0.016										
	(0.013)										
Reform 1998		-0.005									
		(0.012)									
Reform 1998 × Female		0.014									
		(0.012)									
Reform 1999			-0.011								
			(0.012)								
Reform 1999 × Female			0.013								
			(0.011)								
Reform 2000				0.008							
				(0.011)							
Reform 2000 × Female				0.015							
				(0.011)							
Reform 2001					-0.022**						
					(0.010)						
Reform 2001 × Female					0.003						
					(0.011)						
Reform 2002						-0.003					
						(0.011)					
Reform 2002 × Female						-0.002					
						(0.012)					
Reform 2003							0.023*				
							(0.012)				
Reform 2003 × Female							-0.001				
							(0.012)				
Reform 2004								0.021*			
								(0.012)			
Reform 2004 × Female								-0.002			
								(0.014)			
Reform 2005									-0.021		
									(0.014)		
Reform 2005 × Female									-0.001		
									(0.016)		
Reform 2006										0.011	
										(0.016)	
Reform 2006 × Female										-0.013	
										(0.020)	
Reform 2007											-0.005
											(0.007)
Reform 2007 × Female											**0.022****
											(0.011)
Additional Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-Square	0.187	0.187	0.187	0.187	0.187	0.187	0.187	0.187	0.187	0.187	0.171
Number of Obs.	13,013	13,013	13,013	13,013	13,013	13,013	13,013	13,013	13,013	13,013	21,044
F-Test (p-value)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Note: Regressions are estimated with OLS. The different columns represent Placebo tests for the years 1997-2006. Additional controls are as in the preferred specification.Standard errors appear in parentheses and are clustered at the individual level. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. F-Test (p-value) denotes the p-value associated with an F-Test of joint significance of the included controls. Data Source: soep.v33.1, 2016.

Table 3.10: Robustness Test: Period 2006-2008

Variable	Young Individuals
Female	-0.025
	(0.018)
Reform 2007	-0.007
	(0.013)
Female $\times$ Reform 2007	0.036^{*}
	(0.019)
Constant	1.398^{***}
	(0.431)
Additional Controls	Yes
Adj. R-Square	0.193
Number of Obs.	4,306
F-Test (p-value)	0.00

Note: Regressions are estimated with OLS. Additional controls are age, age squared, educational attainment with respect to high school, marital status, number of household members, employment level of partner, a binary indicator variable for linving is West Germany, full-time experience and its suqared, part-time working experience and its squared, a binary indicator variable for being determinated by the former employer, the number of previous years in FTCs, the occupation, the occupational position, the required job training, the firm size, a binary indicator variable for working in public service, and the number of Children. Standard errors appear in parentheses and are clustered at the individual level. ***, ** and * denote significance at the 1%, 5% and/ 10% level, respectively. F-Test (p-value) denotes the p-value associated with an F-Test of joint significance of the included controls. The considered period is restricted to the years 2006 to 2008. Data Source: soep.v33.1, 2016.

Table 3.11: Regression Results DD by Subgroups, Childbearing Age 20-40

Variable	Young, both	Young, with	Young, without	Married Young, without
Dependent Variable: Binary for working in FTC/PC				
Female	0.002	0.014**	0.000	-0.019*
	(0.004)	(0.007)	(0.006)	(0.011)
Reform 2007	0.011***	0.016***	0.000	-0.017
	(0.004)	(0.004)	(0.006)	(0.012)
Reform 2007 × Female	0.015**	0.010	0.019**	0.036**
	(0.006)	(0.008)	(0.010)	(0.018)
Age	-0.014***	-0.017**	-0.001	-0.005
	(0.004)	(0.006)	(0.007)	(0.014)
Age^2	0.000***	0.000***	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Education w.r.t. High School:				
High School	0.004	-0.004	0.012	0.017
	(0.005)	(0.006)	(0.008)	(0.015)
More than High School	-0.010	-0.021**	-0.006	-0.012
	(0.007)	(0.009)	(0.011)	(0.018)
Marital Status:				
Single	0.014***	0.022***	0.008	
	(0.005)	(0.008)	(0.006)	
Widowed	-0.003	-0.030	0.108	
	(0.037)	(0.039)	(0.113)	
Divorced	0.023***	0.009	0.028***	
	(0.007)	(0.010)	(0.011)	
Separated	0.023**	0.001	0.035**	
	(0.010)	(0.014)	(0.014)	
Number of Persons in HH	-0.002	-0.003	0.000	0.001
	(0.002)	(0.002)	(0.002)	(0.009)
Emp. Level of Partner:				
Partner employed FTC	0.016***	0.015**	0.026*	0.012
	(0.006)	(0.007)	(0.014)	(0.019)
Partner employed PC	-0.012***	-0.011***	-0.005	0.008
	(0.004)	(0.004)	(0.011)	(0.015)
No Partner	-0.001	0.016	0.000	0.084
	(0.006)	(0.010)	(0.012)	(0.101)
West Germany	-0.027***	-0.028***	-0.020***	-0.007
	(0.004)	(0.005)	(0.006)	(0.013)
Full-Time Employment Experience	-0.033***	-0.023***	-0.046***	-0.026***
	(0.001)	(0.002)	(0.002)	(0.004)
Full-Time Employment $Experience^2$	0.001***	0.001***	0.002***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Part-Time Employment Experience	-0.010***	-0.016***	-0.003	0.004
	(0.002)	(0.002)	(0.003)	(0.005)
Part-Time Employment $Experience^2$	-0.000	0.000**	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Indicator for Dismissal by former Employer	0.209***	0.196***	0.216***	0.238***
	(0.013)	(0.019)	(0.019)	(0.044)
Number of previous FTCs	0.056***	0.050***	0.065***	0.058***
	(0.003)	(0.004)	(0.004)	(0.008)
Firm Size:				
5 to 20 Employees	0.026***	0.030***	0.022***	-0.001
	(0.005)	(0.007)	(0.008)	(0.017)
More than 20, Less than 200 Employees	0.043***	0.036***	0.051***	0.017
	(0.005)	(0.006)	(0.008)	(0.017)
More than 200 Employees	0.048***	0.046***	0.051***	0.025
	(0.005)	(0.006)	(0.008)	(0.017)
Public Service: No	-0.073***	-0.062***	-0.085***	-0.061***
	(0.005)	(0.006)	(0.007)	(0.013)
Number of Children:				
1-3 Children	0.020***			
	(0.005)			
4 or more Children	0.018	0.005		
	(0.013)	(0.012)		
Constant	0.592***	0.607***	0.432***	0.449*
	(0.070)	(0.109)	(0.106)	(0.238)
Occupational Position	Yes	Yes	Yes	Yes
Occupation	Yes	Yes	Yes	Yes
Required Training	Yes	Yes	Yes	Yes
Adj. R-Square	0.146	0.127	0.174	0.141
Number of Obs.	58,405	32,086	26,319	5,248
F-Test (p-value)	0.00	0.00	0.00	0.00

Note: Regressions are estimated with OLS. In the different columns regression results from the preferred specification for different subgroups are represented. The base category for the educational attainment is *Less than High School*, for the marital status *Married*, for the employment level of the partner *Partner not employed*, for the firm size *Less than 5*, and for the number of Children *No Children*. Standard errors appear in parentheses and are clustered at the individual level. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. F-Test (p-value) denotes the p-value associated with an F-Test of joint significance of the included controls. Data Source: soep.v33.1, 2016.

Table 3.12: Regression Results DD - Subgroups by Income

Variable	Class 1	Class 2	Class 3	Class 4
Dependent Variable: Binary for working in FTC/PC				
Female	-0.062	-0.006	0.005	0.010
	(0.063)	(0.009)	(0.007)	(0.043)
Reform 2007	0.048	0.044***	0.007	-0.008
	(0.075)	(0.011)	(0.005)	(0.019)
Reform 2007 × Female	0.055	0.006	0.002	-0.075
	(0.083)	(0.015)	(0.011)	(0.052)
Age	-0.036	-0.030***	0.002	-0.036
	(0.047)	(0.012)	(0.012)	(0.075)
Age^2	0.001	0.001***	0.000	0.001
	(0.001)	(0.000)	(0.000)	(0.001)
Education w.r.t. High School:				
High School	-0.018	-0.027***	-0.013*	0.037
	(0.031)	(0.009)	(0.008)	(0.024)
More than High School	-0.073	-0.034**	-0.039***	-0.073**
	(0.045)	(0.014)	(0.010)	(0.033)
Number of Persons in HH	-0.025*	-0.004	-0.002	0.015
	(0.013)	(0.003)	(0.002)	(0.012)
Emp. Level of Partner:				
Partner employed FTC	-0.184**	0.016	0.012	0.023
	(0.085)	(0.017)	(0.010)	(0.040)
Partner employed PC	-0.171**	-0.043***	-0.001	-0.009
	(0.071)	(0.011)	(0.006)	(0.019)
No Partner	-0.207**	-0.026**	-0.003	-0.030
	(0.085)	(0.013)	(0.009)	(0.035)
Marital Status:				
Single	0.020	0.017*	0.003	0.049*
	(0.071)	(0.009)	(0.007)	(0.028)
Divorced	0.054	0.042**	-0.010	0.067*
	(0.094)	(0.017)	(0.011)	(0.041)
Separated	-0.098	0.036*	0.008	0.125
	(0.081)	(0.021)	(0.016)	(0.115)
West Germany	-0.128***	-0.005	-0.012*	-0.007
	(0.041)	(0.007)	(0.007)	(0.050)
Full-Time Employment Experience	-0.026***	-0.057***	-0.055***	-0.045***
	(0.010)	(0.003)	(0.003)	(0.014)
Full-Time Employment Experience^2	0.001	0.002***	0.002***	0.002**
	(0.001)	(0.000)	(0.000)	(0.001)
Part-Time Employment Experience	-0.030**	-0.025***	-0.009*	-0.011
	(0.014)	(0.004)	(0.005)	(0.014)
Part-Time Employment Experience^2	0.001	0.000	0.001	0.001
	(0.001)	(0.000)	(0.001)	(0.001)
Indicator for Dismissal by former Employer	0.199**	0.198***	0.252***	-0.018
	(0.091)	(0.020)	(0.028)	(0.038)
Number of previous FTCs	0.055*	0.062***	0.065***	0.068***
	(0.029)	(0.005)	(0.004)	(0.013)
Firm Size:				
5 to 20 Employees	0.034	0.044***	0.008	0.061
	(0.036)	(0.008)	(0.010)	(0.047)
More than 20, Less than 200 Employees	0.046	0.084***	0.022**	-0.015
	(0.038)	(0.009)	(0.010)	(0.030)
More than 200 Employees	0.069*	0.083***	0.038***	0.057**
	(0.041)	(0.009)	(0.009)	(0.026)
Public Service: No	-0.113***	-0.079***	-0.053***	-0.170***
	(0.038)	(0.010)	(0.007)	(0.035)
Number of Children:				
1-3 Children	0.036	0.025***	0.017**	0.006
	(0.047)	(0.009)	(0.007)	(0.029)
4 or more Children	-0.062	-0.047	0.026	-0.009
	(0.091)	(0.035)	(0.024)	(0.065)
Constant	1.614**	0.704***	0.239	0.898
	(0.722)	(0.165)	(0.181)	(1.142)
Occupation	Yes	Yes	Yes	Yes
Adj. R-Square	0.138	0.155	0.150	0.255
Number of Obs.	953	16,866	18,394	1,020
F-Test (p-value)	0.00	0.00	0.00	0.01

Note: Regressions are estimated with OLS. In the different columns regression results from the preferred specification for different subgroups are represented. *Class 1* refers to individuals with a benefit higher than 100%; *Class 2* refers to individuals with a benefit 67-99%; *Class 3* refers to individuals with a benefit 66.9-65%; *Class 4* refers to individuals with a benefit lower than 65%; The base category for the educational attainment is *Less than High School*, for the marital status *Married*, for the employment level of the partner *Partner not employed*, for the firm size *Less than 5*, and for the number of Children *No Children*. Standard errors appear in parentheses and are clustered at the individual level. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. *F*-Test (p-value) denotes the p-value associated with an *F*-Test of joint significance of the included controls. Data Source: soep.v33.1, 2016.

Table 3.13: Regression Results DD - Subgroups by Income Without Children

Variable	Class 1	Class 2	Class 3	Class 4
Dependent Variable: Binary for working in FTC/PC				
Female	-0.062	-0.008	0.003	0.056
	(0.088)	(0.011)	(0.008)	(0.050)
Reform 2007	-0.017	0.028**	-0.002	0.050*
	(0.093)	(0.014)	(0.008)	(0.027)
Reform 2007 × Female	0.082	0.038**	0.015	-0.149**
	(0.128)	(0.019)	(0.013)	(0.066)
Age	0.029	-0.021	0.007	-0.017
	(0.096)	(0.017)	(0.016)	(0.093)
Age^2	-0.001	0.001*	-0.000	0.000
	(0.002)	(0.000)	(0.000)	(0.001)
Education w.r.t. High School:				
High School	-0.017	-0.023*	0.001	0.043
	(0.080)	(0.012)	(0.013)	(0.075)
More than High School	-0.135	-0.026	-0.022	-0.039
	(0.116)	(0.019)	(0.015)	(0.071)
Number of Persons in HH	-0.038	0.001	-0.000	0.025
	(0.033)	(0.004)	(0.003)	(0.016)
Emp. Level of Partner:				
Partner employed FTC	0.253	0.041	0.031	0.019
	(0.163)	(0.028)	(0.022)	(0.106)
Partner employed PC	0.347***	-0.018	-0.000	-0.059
	(0.111)	(0.021)	(0.016)	(0.065)
No Partner	0.265**	-0.010	-0.002	-0.076
	(0.125)	(0.021)	(0.017)	(0.070)
Marital Status:				
Single	0.080	0.011	0.004	0.049
	(0.132)	(0.012)	(0.008)	(0.031)
Divorced	0.039	0.053**	0.002	0.075
	(0.178)	(0.026)	(0.014)	(0.046)
Separated	0.035	0.038	0.025	0.214
	(0.229)	(0.036)	(0.021)	(0.135)
West Germany	-0.112	0.011	-0.022**	-0.050
	(0.074)	(0.009)	(0.009)	(0.086)
Full-Time Employment Experience	-0.059**	-0.069***	-0.064***	-0.016
	(0.025)	(0.004)	(0.004)	(0.022)
Full-Time Employment Experience^2	0.003	0.003***	0.003***	-0.000
	(0.002)	(0.000)	(0.000)	(0.001)
Part-Time Employment Experience	-0.009	-0.011*	-0.010*	-0.020
	(0.032)	(0.007)	(0.006)	(0.017)
Part-Time Employment Experience^2	-0.004	-0.001	0.001	0.002
	(0.004)	(0.001)	(0.001)	(0.002)
Indicator for Dismissal by former Employer	0.334	0.196***	0.226***	-0.001
	(0.219)	(0.025)	(0.041)	(0.073)
Number of previous FTCs	0.060	0.077***	0.071***	0.068***
	(0.067)	(0.008)	(0.006)	(0.019)
Firm Size:				
5 to 20 Employees	0.051	0.033***	0.022*	-0.038
	(0.131)	(0.012)	(0.012)	(0.036)
More than 20, Less than 200 Employees	0.029	0.083***	0.043***	-0.017
	(0.135)	(0.012)	(0.012)	(0.036)
More than 200 Employees	-0.005	0.083***	0.047***	0.025
	(0.137)	(0.013)	(0.012)	(0.031)
Public Service: No	-0.072	-0.074***	-0.062***	-0.183***
	(0.075)	(0.012)	(0.009)	(0.052)
Widowed		-0.322***	0.050*	
		(0.024)	(0.027)	
Constant	0.632	0.516**	0.152	0.436
	(1.327)	(0.235)	(0.233)	(1.360)
Occupation	Yes	Yes	Yes	Yes
Adj. R-Square	0.074	0.183	0.163	0.276
Number of Obs.	241	9,641	10,761	419
F-Test (p-value)	0.00	0.00	0.00	0.01

Note: Regressions are estimated with OLS. In the different columns regression results from the preferred specification for different subgroups are represented. *Class 1* refers to individuals with a benefit higher than 100%; *Class 2* refers to individuals with a benefit 67-99%; *Class 3* refers to individuals with a benefit 66.9-65%; *Class 4* refers to individuals with a benefit lower than 65%; The base category for the educational attainment is *Less than High School*, for the marital status *Married*, for the employment level of the partner *Partner not employed*, for the firm size *Less than 5*, and for the number of Children *No Children*. Standard errors appear in parentheses and are clustered at the individual level. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. F-Test (p-value) denotes the p-value associated with an F-Test of joint significance of the included controls. Data Source: soep.v33.1, 2016.

Table 3.14: Regression Results DD by Subgroups - New Hires

Variable	Young, both	Young, with	Young, without
Dependent Variable: Binary for working in FTC/PC			
Female	-0.013	-0.041	-0.009
	(0.034)	(0.060)	(0.043)
Reform 2007	0.054	0.123**	-0.024
	(0.033)	(0.056)	(0.040)
Reform 2007 × Female	0.082*	0.005	0.134**
	(0.045)	(0.070)	(0.060)
Age	-0.051	-0.081	-0.008
	(0.037)	(0.056)	(0.052)
Age^2	0.001	0.002	0.000
	(0.001)	(0.001)	(0.001)
Education w.r.t. High School:			
High School	-0.043	-0.070	-0.041
	(0.032)	(0.046)	(0.047)
More than High School	-0.031	0.036	-0.096
	(0.054)	(0.076)	(0.074)
Marital Status:			
Single	0.034	0.034	0.004
	(0.038)	(0.055)	(0.057)
Widowed	0.119	0.179	
	(0.424)	(0.394)	
Divorced	0.039	0.054	-0.021
	(0.065)	(0.081)	(0.118)
Separated	0.090	0.098	0.061
	(0.074)	(0.094)	(0.113)
Number of Persons in HH	0.001	-0.016	0.007
	(0.010)	(0.016)	(0.013)
Emp. Level of Partner:			
Partner employed FTC	0.046	0.007	0.209**
	(0.059)	(0.077)	(0.106)
Partner employed PC	-0.044	-0.026	0.040
	(0.041)	(0.051)	(0.089)
No Partner	0.015	0.057	0.099
	(0.047)	(0.070)	(0.091)
West Germany	-0.070***	-0.118***	-0.044
	(0.027)	(0.042)	(0.036)
Full-Time Employment Experience	-0.010	0.006	-0.038**
	(0.010)	(0.014)	(0.016)
Full-Time Employment Experience^2	0.000	-0.001	0.002*
	(0.001)	(0.001)	(0.001)
Part-Time Employment Experience	0.003	-0.022	0.026
	(0.017)	(0.024)	(0.022)
Part-Time Employment Experience^2	0.000	0.003	-0.002
	(0.002)	(0.003)	(0.003)
Indicator for Dismissal by former Employer	0.029	0.024	0.032
	(0.030)	(0.048)	(0.038)
Number of previous FTCs	0.032	0.003	0.059*
	(0.020)	(0.027)	(0.033)
Firm Size:			
5 to 20 Employees	0.173***	0.175***	0.168***
	(0.037)	(0.055)	(0.051)
More than 20, Less than 200 Employees	0.290***	0.249***	0.316***
	(0.036)	(0.054)	(0.050)
More than 200 Employees	0.325***	0.379***	0.278***
	(0.037)	(0.056)	(0.050)
Public Service: No	-0.233***	-0.153***	-0.297***
	(0.034)	(0.053)	(0.044)
Number of Children:			
1-3 Children	0.033		
	(0.033)		
4 or more Children	-0.173	-0.173*	
	(0.105)	(0.101)	
Constant	0.975*	1.343	0.447
	(0.525)	(0.825)	(0.737)
Occupation	Yes	Yes	Yes
Required Training	Yes	Yes	Yes
Adj. R-Square	0.108	0.100	0.140
Number of Obs.	1,792	795	997
F-Test (p-value)	0.00	0.00	0.00

Note: Regressions are estimated with OLS. In the different columns regression results from the preferred specification for different subgroups are represented. Results for the different specifications can be found in the Appendix. The base category for the educational attainment is *Less than High School*, for the marital status *Married*, for the employment level of the partner *Partner not employed*, for the firm size *Less than 5*, and for the number of children *No children*. Standard errors appear in parentheses and are clustered at the individual level. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. *F*-Test (p-value) denotes the p-value associated with an F-test of joint significance of the included controls. Data Source: soep.v33.1, 2016.

Chapter 4

Population Adjustment to Asymmetric Labour Market Shocks in India - A Comparison to Europe and the United States at Two Different Regional Levels

4 Population Adjustment to Asymmetric Labour Market Shocks in India - A Comparison to Europe and the United States at Two Different Regional Levels

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4.1 Introduction

Internal migration can be an important component for adjusting asymmetric regional labour market shocks. For a fast-developing economy like India, which is also experiencing rapid population growth, efficient internal migration of labour may be even more important (Lagakos, 2020). Still, in a large country such as India with different language groups, internal migration may also face political and administrative barriers as documented in Aggarwal et al. (2020), Bhagat (2012), Borhade (2012) or Kone et al. (2018).

In this paper, we estimate how net migration, proxied by regression-controlled population change in a region, reacts to regional labour market shocks in India. We measure asymmetric regional labour market shocks by changes in the ratio of the regional non-employment rate to the average non-employment rate of all Indian regions as well as by changes in the ratio of the average full-time wage in a region to the average wage of all Indian regions. We use both states/union territories and districts as regional units.[1] Based on regressions using regional and year fixed effects, we find that Indian workers respond to asymmetric regional labour market conditions. Indeed, when comparing our results to those obtained for the United States and the European Union applying the same methodology as in Jauer et al. (2019), we find that regional adjustment in India occurs primarily at the district but not at the state level, whereas it occurs at both of these levels in the United States and in Europe. This finding is not inconsistent with concerns raised in the literature on barriers to mobility: maybe the dynamics of the Indian economy requires much more labour mobility for India to unleash its economic potential.

[1]In the following, when we refer to states this is supposed to include the union territories.

During the last two decades, India has seen significant macroeconomic and labour market changes: India has seen larger population growth since the year 2000 than the United States, the European Union, or China, but its GDP growth has been below the one of China since the late 2000s (see Figures 4.1 and 4.2). This raises the question whether India is making full use of its labour market potential. Indeed, the employment to population ratio for people older than 15 years of age has been decreasing for the last two decades in India and is now below the one of the United States, the European Union and China (Figure 4.3), see also Verick (2014). The unemployment rate has increased recently (Figure 4.4), although—given the lack of a European or U.S. style unemployment benefit system—we have doubts whether it is as meaningful as a statistic here as the non-employment rate, which will be our preferred statistic to measure (the inverse of) labour market tightness. For the employed, there have been significant structural shifts: India has experienced a decrease in the (still high) share of agricultural employment. This is not only reflected in an increase in the share of service employment: in striking contrast to the United States and the European Union, India and China have experienced industrialisation of their workforces in the first decade of the 21st century and slightly beyond (Figures 5 to 7). India may thus experience a form of development similar to the Lewis (1954) model, for which internal migration is a crucial component.

The paper is structured as follows. Section 4.2 describes our data set and presents descriptive statistics in the form of graphs. Section 4.3 presents the regression results. Section 4.4 concludes.

4.2 Data and Descriptive Statistics

We use individual-level survey data from the Employment and Unemployment Survey (EUS) by the National Sample Survey Office (NSSO) of India, rounds 60 (collected from January 2004 to June 2004), 62 (collected from July 2005 to June 2006), 64 (collected from July 2007 to June 2008), 66 (collected from July 2009 to June 2010), and 68 (latest available, collected from July 2011 to June 2012). Because round 60 was only collected during 6 instead of 12 months, we will check the sensitivity of our results with respect to exclusion or inclusion of round 60. Round 61 is excluded because our estimating equation will contain a lag structure and we want to maintain a similar (two-year) lag throughout the sample.

Using sampling weights, we build regional-level data (at the state/union territory or district level) for the population growth factor, the non-employment rate (1 minus the employment-population ratio) and the unemployment rate. In doing that, we only consider people of working age (15-64). Using sampling weights, we also generate the average wage per region as a proxy for earnings potential. Because we do not have information on hours of work, we only use full-time workers who usually work at least 5 days per week full-time.

We exclude the following small union territories: Andaman and Nicobar Islands, Lakshadweep (both islands), and Pondicherry (set of geographically disconnected territories). Because of changes to districts and inconsistencies in the data, Delhi and Goa are treated as a single entity in the district data. The following districts are excluded due to lack of wage information: Lakhisarai (Bihar), Upper Siang (Arunachal Pradesh), and Tamenglong (Manipur). We also excluded Leh Ladakh, Kargil, and Punch (all Jammu and Kashmir), because data for these districts are only available in round 68 (collected from July 2011 to June 2012) of the EUS survey. This leaves us with 32 states/union territories and 570 districts, which we observe bi-annually in 5 different years over a time period of about 8 years.[2]

The size of the population is heterogeneous across states and districts as exhibited in Figure 4.8 and Figure 4.9. Average wages increased in virtually all states after 2008 (Figure 4.10). However, the increase in wages was also accompanied by regional diversion from 2008 to 2012, whereas there seems to have been regional wage conversion between 2004 and 2008, see the corresponding coefficients of variation in Figure 4.20. When considering wages by district, there also seems to be increasing diversion together with wage increases after 2008 (even when ignoring the outlier, see Figure 4.11 and the corresponding coefficients of variation in Figure 4.21). Himanshu (2017) also reports a “rapid acceleration” of wages “during 2008-2013” (p. 309).

On the other hand, there seems to be a convergence in the non-employment rates by both states and districts, despite of rising non-employment rates (Figures 4.12 and 4.13, for the corresponding coefficients of variation, see Figures 4.18 and 4.19). The dispersion of the regional unemployment rate seems to move more erratically over time, especially when plotted by dis-

[2]District-level territorial reforms in the period under consideration were taken into account as follows: we used the districts from round 60 of the EUS-NSSO as a basis. In most cases, it was clear from which district the new district had been created and we assigned it to the original district. Exceptions are the district of Mewat (state: Haryana) and the district of Baksa (state: Assam), where the district of origin was not clearly identifiable. Here we have merged the new districts and all the original districts. A detailed list can be requested from the authors.

trict (Figure 4.14 and Figure 4.15). There appears to be an increase in the dispersion when plotted by state (Figure 4.14), but we consider the non-employment statistic to be more reliable than the unemployment statistic. Indeed, as Figures 4.16 and 4.17 show, there is a clear increase in the non-employment rate over time (when averaged over states and districts), whereas there is no such clear trend for the unemployment rate.

4.3 Methodology and Results

Following Jauer et al. (2019), we estimate the following regression with the regional population growth factor on the left hand side and the region's ratio of its unemployment/non-employment rate (ur) to the national average as well as the ratio of the region's wage rate (y) to the national average on the right hand side. The estimating equation is:

$$ln\left(\frac{pop_{it}}{pop_{it-2}}\right) = \alpha_0 + \alpha_1 ln\left(\frac{ur_{it-2}}{ur_{nt-2}}\right) + ln\left(\frac{y_{it-2}}{y_{nt-2}}\right) + \eta_t + \mu_i + \varepsilon_{it} \tag{4.1}$$

Because we have bi-annual regional panel data, we include both region and time fixed effects (FE), μ_i and η_t, respectively. Because the national averages in the denominators on the right hand side are constant between regions, they are taken account of by the year fixed effects. If the region and time fixed effects take account of natural population growth, using the population growth factor on the left hand side – regression-adjusted by region and time effects – will effectively measure population change due to net migration.[3]

$$\begin{aligned} ln\left(\frac{pop_{it}}{pop_{it-2}}\right) - \eta_t - \mu_i &= ln\left(\frac{\Delta^t_{t-2}pop_{it} + pop_{it-2}}{pop_{it-2}}\right) - \eta_t - \mu_i \\ &\approx ln\left(\frac{mig_{it,t-2} + pop_{it-2}}{pop_{it-2}}\right) \end{aligned} \tag{4.2}$$

[3]We have also experimented with proxying bi-annual natural population growth by adding the number of people aged 13 and 14 years of age and subtracting the number of people aged 63 and 64 years of age at the state and district level for the base year. Subtracting our natural population growth proxy from the observed population growth – and taking this difference as dependent variable – hardly makes any difference to our point estimates of the coefficients of the unemployment/non-employment rate or the wage rate in the fixed-effects regressions. This supports our working hypothesis that region and time fixed effects together act as an adequate control for natural population growth in our model during our observation period.

Under these assumptions, we follow Jauer et al. (2019) and interpret the coefficients on the unemployment/non-employment rate and on the wage as the reactions of net migration to regional labour market shocks. Because of the log-log specification, the coefficient on the wage can be interpreted as an elasticity. Similarly, the coefficient on the unemployment/non-employment rate is an elasticity, but here we are more interested in how much of an increase in non-employment in a region can possibly be adjusted by net migration (discussed below).

Table 4.1 shows ordinary least squares (OLS, first two columns, the latter restricted to the population up to age 50) and fixed-effects (FE, last two columns, the latter restricted to the population up to age 50) regression results at the state level. The upper panel of the table presents the specifications with lagged relative unemployment and the lower panel the specifications with lagged relative non-employment as measure of labour market tightness. Within these panels the upper (lower) block refers to rounds 62 (60) to 68 of the EUS, hence years 2005 (2004) to 2012. In the OLS results without region fixed effects, which exploit both within- and between-state variation in the impact variables, none of the unemployment, non-employment nor wage variables are statistically significant. Still, the coefficients have the expected signs.
In the fixed-effects regressions, the coefficients for state unemployment and non-employment are still statistically insignificant, but the wage rate is statistically significant. The interpretation for the FE coefficients in the third column of Table 4.1 is that a one percent increase in the wage of a region increases the population growth factor by approximately 0.45 percent (coefficients are rather similar across the panels in the third column). This estimate is larger than the estimates reported by Jauer et al. (2019) for the United States and the European Union, which are statistically insignificant in many cases. However, these authors have a one-year time lag. Hence, in order to produce comparable results for the Unites States and the European Union, in Appendix Table C.1 we use the data of Jauer et al. (2019) and re-estimate their main models with a two-year lag. Still, the wage effect estimates for the United States and the European Union remain smaller than the ones for India. When we add round 62 and the lagged variables from round 60 to the sample as a robustness check (the second blocks in the panels of Table 4.1), we mostly obtain similar results for both OLS and FE estimates.

Using Indian districts instead of states as units of analysis (Table 4.2), the coefficient of the non-employment rate becomes statistically significant, although the coefficient of the unemployment rate is still statistically insignificant with a point estimate close to zero. Again, results are qualitatively robust to the inclusion of round 62 and the lagged variables from round 60.

Results in general are also qualitatively and quantitatively similar when restricting the sample to the population up to age 50 (Table 4.1, columns 2 and 4 at the state level and Table 4.2 columns 2 and 4 at the district level), which might be more mobile. The coefficients are only a bit larger in most cases. This might be explained by India being a young country, so that the cohorts above age 50 are comparatively small, which lessens their influence on the estimates for the total working age population.[4]

How can we interpret the size of the estimate for the unemployment or non-employment rate? In order to simulate how much of an increase in non-employment in a region can possibly be adjusted by net migration, Tables 4.3 and 4.4 show what a one percent increase in unemployment or non-employment amounts to in absolute numbers and set this in relation to the migration-induced population change of α_1 percent. The inverse ratio between these two is the fraction of the unemployment or non-employment change that can at most be adjusted by migration (population change). This upper bound would only be reached if all migration (population change) were labour market related and actually offset the asymmetric shock. Tables 4.5 and 4.6 present the corresponding results for the United States and the European Union based on the data used in Jauer et al. (2019), but with a two-year lag structure, as we have in the data for India. The regression results on which these simulations are based are reported in Table C.1.

In Table 4.3, which reports simulations at the state level, none of the coefficients underlying the simulations is statistically significant and the simulated percent of the shock adjusted due to migration changes sign. However, when considering the district level, the simulated adjustments based on the statistically significant coefficients, which are exclusively the coefficients of non-employment, are consistently between 28 and 37 percent. When comparing the results for India with those for the United States and the European Union in Tables 4.5 and 4.6, we make two key observations. First, whereas none of the estimates at the state level are statistically significant for India, for the United States and Europe, all the estimates both at the state/NUTS-1 and the

[4]At the district level, we also conducted the analysis by gender. Results can be found in Appendix C, Tables C.2 and C.3. Again, only coefficients of the fixed-effects regressions for non-employment are significant. Comparing men and women, point estimates for women are somewhat lower in absolute terms than for men using the whole sample (Table C.2), but for non-employment (but not for the wage) slightly larger when restricting the sample to the population up to age 50 (Table C.3). In Table C.4, we also report separate estimates for population changes by social background, where disadvantaged “classes” (abbreviated OBC in the EUS-NSSO), “scheduled tribes” (ST) and “scheduled casts” (SC), again as defined in the EUS-NSSO, all together form the disadvantaged group, which amounts to about two thirds of the Indian population according to unweighted survey statistics, and “others”, as defined in the EUS-NSSO, form the alternative group. The point estimates shown in Table C.4 show that although both groups react to district non-employment and wage differentials, the point estimates for the disadvantaged groups are larger than for the “other” group.

district level are statistically significant and the adjustments are of similar size, even larger at the state than at the district level. This is consistent with limited adjustment to non-employment disparities across state boundaries in India when compared to the United States and the European Union. Second, whereas we only observe an adjustment to non-employment, but not to unemployment disparities in India, in the United States and in Europe, the adjustment is larger with respect to unemployment than with respect to non-employment.

4.4 Conclusion

In this paper, we have used the EUS-NSSO data to create regional panel data sets for both Indian states and districts. Based on this panel, we have estimated how the population in these regions adjusts to asymmetric labour market shocks within a two-year time period. These asymmetric labour market shocks have been proxied from the same data source using the average wage and unemployment or non-employment rate in the state or district, lagged by two years.

Based on fixed-effects models, we find that Indian workers migrate (proxied by regression-adjusted population change) in response to wage and non-employment shocks. However, the unemployment rate does not seem to be a very reliable statistic in this context. When compared with results applying the same methodology using data for the United States and the European Union for a similar time period (Jauer et al., 2019), we find no significant response of Indian workers to non-employment disparities across Indian states, but only to Indian districts, whereas the response to disparities is similar across states/NUTS-1 regions and districts in the United States and in Europe.

Disclosures and Declarations

No funding was received to assist with the preparation of this manuscript. The authors have no conflicting interests. A copy of the manuscript has been sent by email to the National Sample Survey Office (NSSO) of India: nssunit.dsdd@mospi.gov.in.

Tables

Table 4.1: Regressions at the State Level

	OLS	OLS U50	FE	FE U50
Specifications with Lagged Relative Unemployment				
Unemployment, Rounds 62-68				
log rel. unemp.	-0.011	-0.010	0.008	0.013
(s.e.)	(0.010)	(0.011)	(0.020)	(0.019)
log rel. wage	0.007	0.008	0.449***	0.502***
(s.e.)	(0.005)	(0.005)	(0.126)	(0.120)
Constant	0.072***	0.064***	-0.412***	-0.472***
(s.e.)	(0.021)	(0.022)	(0.139)	(0.131)
R2 / R2 within	0.065	0.054	0.398	0.466
No. regions	32	32	32	32
No. observations	96	96	96	96
Unemployment, Rounds 60-68				
log rel. unemp.	-0.010	-0.007	0.003	0.010
(s.e.)	(0.013)	(0.013)	(0.023)	(0.021)
log rel. wage	0.003	0.003	0.456***	0.510***
(s.e.)	(0.005)	(0.005)	(0.099)	(0.101)
Constant	0.077***	0.070***	-0.421***	-0.482***
(s.e.)	(0.022)	(0.023)	(0.102)	(0.102)
R2 / R2 within	0.059	0.041	0.349	0.400
No. regions	32	32	32	32
No. observations	128	128	128	128
Specifications with Lagged Relative Non-Employment				
Non-Employment, Rounds 62-68				
log rel. non-emp.	-0.018	-0.019	-0.096	-0.069
(s.e.)	(0.053)	(0.051)	(0.130)	(0.124)
log rel. wage	0.007	0.008	0.441***	0.496***
(s.e.)	(0.005)	(0.006)	(0.131)	(0.124)
Constant	0.074***	0.066***	-0.408***	-0.471***
(s.e.)	(0.022)	(0.023)	(0.143)	(0.134)
R2 / R2 within	0.058	0.049	0.406	0.465
No. regions	32	32	32	32
No. observations	96	96	96	96
Non-Employment, Rounds 60-68				
log rel. non-emp.	0.001	0.024	-0.033	0.009
(s.e.)	(0.048)	(0.048)	(0.138)	(0.128)
log rel. wage	0.003	0.003	0.456***	0.506***
(s.e.)	(0.005)	(0.006)	(0.101)	(0.103)
Constant	0.079***	0.073***	-0.422***	-0.478***
(s.e.)	(0.022)	(0.024)	(0.107)	(0.106)
R2 / R2 within	0.054	0.041	0.350	0.398
No. regions	32	32	32	32
No. observations	128	128	128	128

Note: Regressions are estimated by pooled ordinary least squares (OLS) and fixed effects (FE). U50 refers to a sub-sample not older than 50 years of age. Standard errors clustered at the state level appear in parentheses. All regressions include year fixed effects. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Data Source: Indian EUS-NSSO.

Table 4.2: Regressions at the District Level

	OLS	OLS U50	FE	FE U50
Specifications with Lagged Relative Unemployment				
Unemployment, Rounds 62-68				
log rel. unemp.	-0.002	-0.001	-0.001	0.001
(s.e.)	(0.003)	(0.003)	(0.005)	(0.005)
log rel. wage	0.013***	0.013***	0.229***	0.259***
(s.e.)	(0.004)	(0.004)	(0.022)	(0.022)
Constant	0.037***	0.029***	-0.005	-0.021**
(s.e.)	(0.008)	(0.008)	(0.008)	(0.008)
R2 / R2 within	0.013	0.013	0.132	0.151
No. regions	570	570	570	570
No. observations	1,590	1,587	1,590	1,587
Unemployment, Rounds 60-68				
log rel. unemp.	-0.004	-0.003	-0.002	0.001
(s.e.)	(0.003)	(0.003)	(0.004)	(0.005)
log rel. wage	0.026***	0.027***	0.351***	0.373***
(s.e.)	(0.006)	(0.006)	(0.035)	(0.036)
Constant	0.049***	0.057***	-0.034***	-0.027**
(s.e.)	(0.014)	(0.015)	(0.011)	(0.011)
R2 / R2 within	0.024	0.025	0.252	0.266
No. regions	570	570	570	570
No. observations	2,081	2,078	2,081	2,078
Specifications with Lagged Relative Non-Employment				
Non-Employment, Rounds 62-68				
log rel. non-emp.	-0.019	-0.025*	-0.126***	-0.138***
(s.e.)	(0.014)	(0.015)	(0.030)	(0.032)
log rel. wage	0.014***	0.014***	0.235***	0.266***
(s.e.)	(0.004)	(0.004)	(0.022)	(0.023)
Constant	0.039***	0.028***	-0.024***	-0.042***
(s.e.)	(0.008)	(0.008)	(0.009)	(0.009)
R2 / R2 within	0.016	0.015	0.151	0.169
No. regions	570	570	570	570
No. observations	1,708	1,707	1,708	1,707
Non-Employment, Rounds 60-68				
log rel. non-emp.	-0.021	-0.020	-0.162***	-0.153***
(s.e.)	(0.017)	(0.017)	(0.026)	(0.026)
log rel. wage	0.028***	0.029***	0.360***	0.388***
(s.e.)	(0.006)	(0.006)	(0.031)	(0.033)
Constant	0.064***	0.070***	-0.049***	-0.048***
(s.e.)	(0.014)	(0.014)	(0.012)	(0.012)
R2 / R2 within	0.031	0.032	0.271	0.292
No. regions	570	570	570	570
No. observations	2,273	2,272	2,273	2,272

Note: Regressions are estimated by pooled ordinary least squares (OLS) and fixed effects (FE). U50 refers to a sub-sample not older than 50 years of age. Standard errors clustered at the district level appear in parentheses. All regressions include year fixed effects. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Data Source: Indian EUS-NSSO.

Table 4.3: Simulated Unemployment/Non-Employment Adjustment due to Migration at the State Level (Based on Fixed-Effect Estimates)

Specification	Coefficient	Standard Error	Average Number of Unemp./Non-Emp.	Average Population	1 % Change in Unemp./Non-Emp.	Migration Induced Pop. Change	UE/NON-E Adj. due to Mig (%)
Unemployment							
Rounds 60-68	(0.003)	0.023	319,437	20,416,288	3,194	(-524)	(-16)
Rounds 60-68, U50	(0.010)	0.021	314,671	17,721,014	3,147	(-1,711)	(-54)
Rounds 62-68	(0.008)	0.020	312,383	20,877,478	3,124	(-1,745)	(-56)
Rounds 62-68, U50	(0.013)	0.019	308,319	18,084,318	3,083	(-2,424)	(-79)
Non-Employment							
Rounds 60-68	(-0.033)	0.138	9,073,555	20,416,288	90,736	(6,649)	(7)
Rounds, 60-68, U50	(0.009)	0.128	8,017,520	17,721,014	80,175	(-1,611)	(-2)
Rounds 62-68	(-0.096)	0.130	9,426,386	20,877,478	94,264	(19,997)	(21)
Rounds 62-68, U50	(-0.069)	0.124	8,319,259	18,084,318	83,193	(12,462)	(15)

Note: The rows contain results based on regressions using either the unemployment (Unemp., UE) or non-employment (Non-Emp., NON-E) rate as explanatory variable. Rounds 60-68 and Rounds 62-68 stand for results based on using the EUS-NSSO rounds 60-68 and 62-68, respectively (including lagged variables). U50 refers to samples of individuals aged 15-50, whereas the default sample uses the working-age population aged 15-64. Because none of the coefficients is significant, the simulated changes/adjustments appear in parentheses. Data Source: EUS-NSSO.

Table 4.4: Simulated Unemployment/Non-Employment Adjustment due to Migration at the District Level (Based on Fixed-Effect Estimates)

Specification	Coefficient	Standard Error	Average Number of Unemp./Non-Emp.	Average Population	1 % Change in Unemp./Non-Emp.	Migration Induced Pop. Change	UE/NON-E Adj. due to Mig (%)
Unemployment							
Rounds 60-68	(-0.002)	0.004	19,102	1,190,959	191	(29)	(15)
Rounds 60-68, U50	(0.001)	0.005	18,844	1,033,651	188	(-11)	(-6)
Rounds 62-68	(-0.001)	0.005	18,361	1,201,157	184	(14)	(7)
Rounds 62-68, U50	(0.001)	0.005	18,145	1,040,755	181	(-10)	(-5)
Non-Employment							
Rounds 60-68	-0.162	0.026	510,440	1,148,707	5,104	1,864	37
Rounds 60-68, U50	-0.153	0.026	451,154	997,302	4,512	1,527	34
Rounds 62-68	-0.126	0.030	529,332	1,172,602	5,293	1,482	28
Rounds 62-68, U50	-0.138	0.032	467,347	1,016,076	4,673	1,400	30

Note: The rows contain results based on regressions using either the unemployment (Unemp., UE) or non-employment (Non-Emp., NON-E) rate as explanatory variable. Rounds 60-68 and Rounds 62-68 stand for results based on using the EUS-NSSO rounds 60-68 and 62-68, respectively (including lagged variables). U50 refers to samples of individuals aged 15-50, whereas the default sample uses the working-age population aged 15-64. Results based on insignificant coefficients are presented in parentheses. Data Source: EUS-NSSO.

Table 4.5: Simulated Unemployment/Non-Employment Adjustment due to Migration at the District Level (Based on Fixed-Effect Estimates), EU-27, Eurozone, and USA, Larger Regions 2006-2016

Specification	Coefficient	Average Number of Unemp./Non-Emp.	Average Population	1 % Change in Unemp./Non-Emp.	Migration Induced Pop. Change	UE/NON-E Adj. due to Mig (%)
Unemployment						
EU-27/EFTA NUTS-1	-0.030	222,675	3,423,717	2,227	1,027	46
Eurozone NUTS-1	-0.028	253,040	3,512,915	2,530	984	39
USA States	-0.021	242,253	4,034,056	2,423	847	35
Non-Employment						
EU-27/EFTA NUTS-1	-0.058	1,383,131	4,091,638	13,831	2,373	17
Eurozone NUTS-1	-0.095	1,199,681	3,492,804	11,997	3,318	28
USA States	-0.077	1,358,869	4,034,056	13,589	3,095	23

Note: The rows contain results based on regressions using either the unemployment (Unemp., UE) or non-employment (Non-Emp., NON-E) rate as explanatory variable. All coefficients presented in this table are statistically significant. Data Source: European Labour Force Survey, Eurostat Regional Database, American Community Survey.

Table 4.6: Simulated Unemployment/Non-Employment Adjustment due to Migration at the District Level (Based on Fixed-Effect Estimates), EU-27, Eurozone, and USA, Smaller Regions 2006-2016

Specification	Coefficient	Average Number of Unemp./Non-Emp.	Average Population	1 % Change in Unemp./Non-Emp.	Migration Induced Pop. Change	UE/NON-E Adj. due to Mig (%)
Unemployment						
EU-27/EFTA NUTS-2	-0.027	83,125	1,277,951	831	345	42
Eurozone NUTS-2	-0.026	92,067	1,277,911	921	332	36
USA SuperPUMA	-0.015	53,717	907,276	537	136	25
Non-Employment						
EU-27/EFTA NUTS-2	-0.096	427,119	1,274,914	4,271	1,224	29
Eurozone NUTS-2	-0.088	437,531	1,273,134	4,375	1,120	26
USA SuperPUMA	-0.034	306,694	907,276	3,067	308	10

Note: The rows contain results based on regressions using either the unemployment (Unemp., UE) or non-employment (Non-Emp., NON-E) rate as explanatory variable. All coefficients presented in this table are statistically significant. Data Source: European Labour Force Survey, Eurostat Regional Database, American Community Survey.

4.5 Graphs

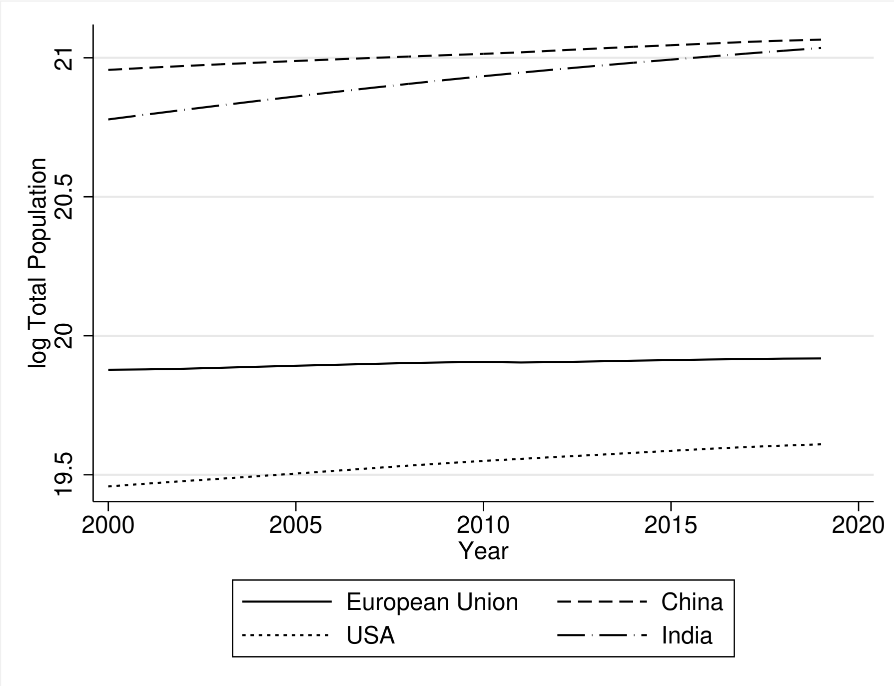

Figure 4.1: Population by Country. Data Source: https://data.worldbank.org.

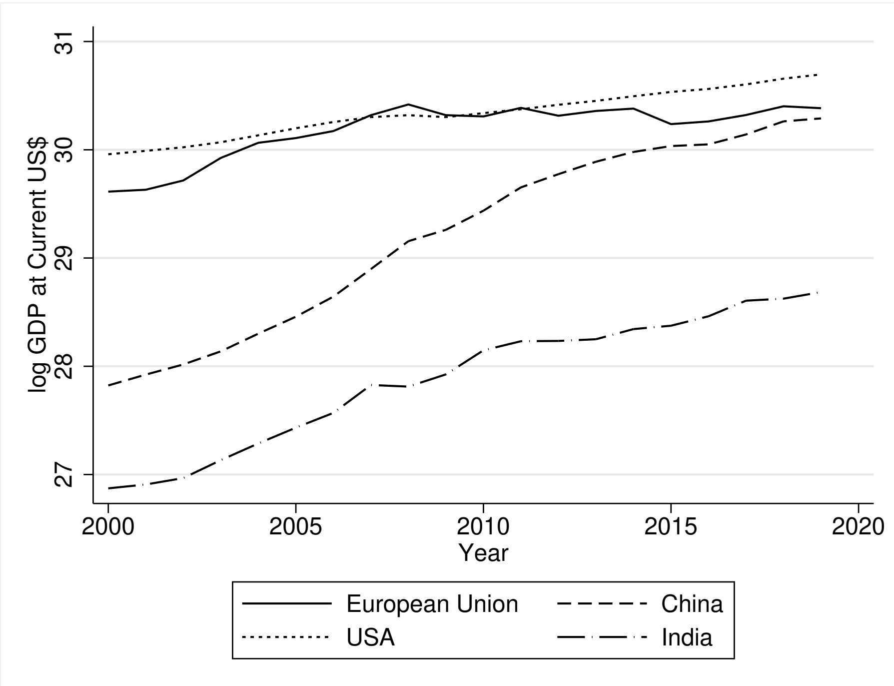

Figure 4.2: GDP by Country. Data Source: https://data.worldbank.org.

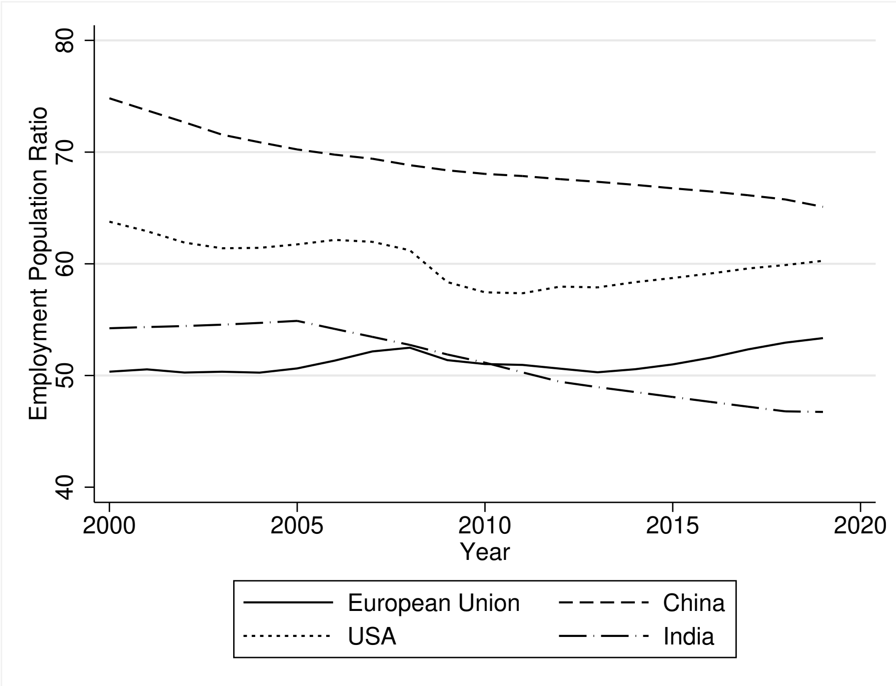

Figure 4.3: Employment to Population Ratio by Country. Data Source: https://data.worldbank.org.

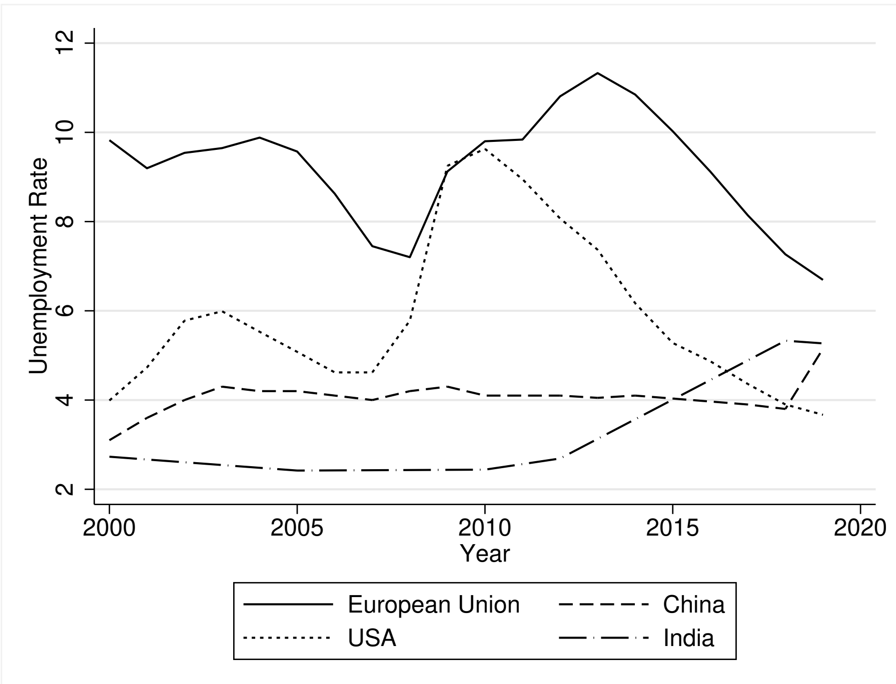

Figure 4.4: Unemployment Rates by Country. Data Source: https://data.worldbank.org.

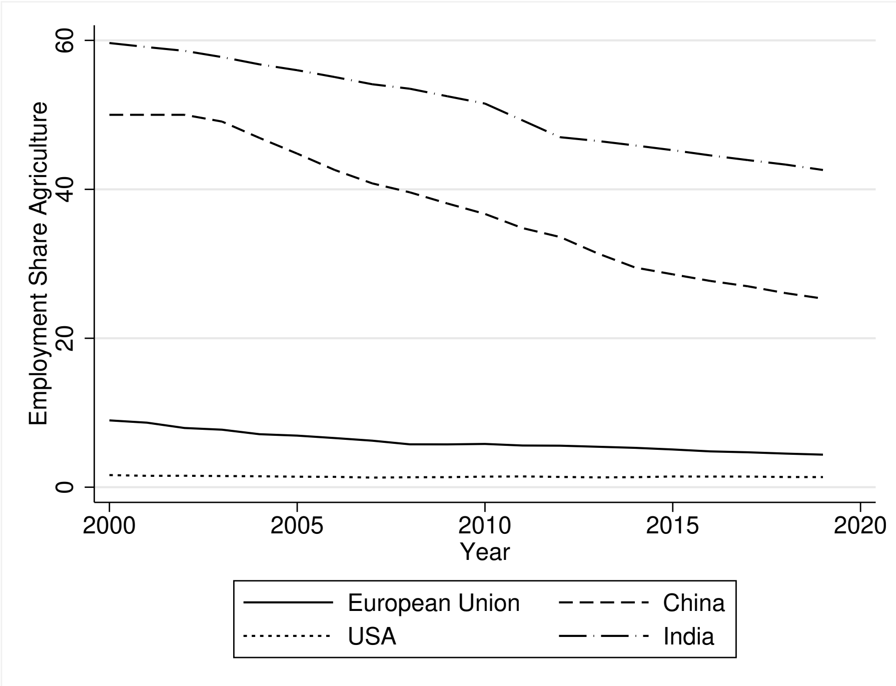

Figure 4.5: Employment Share Agriculture by Country. Data Source: https://data.worldbank.org.

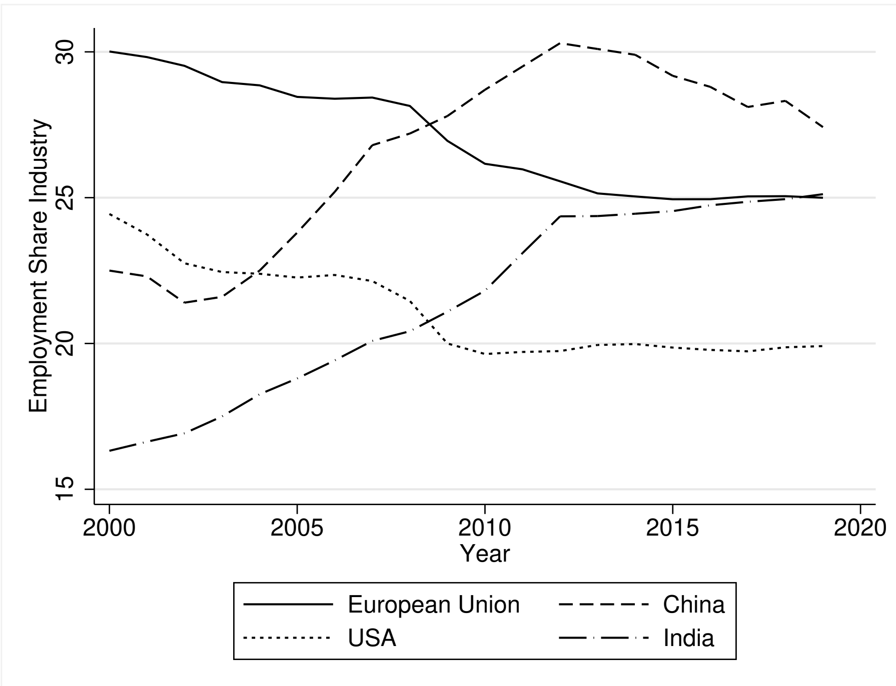

Figure 4.6: Employment Share Industry by Country. Data Source: https://data.worldbank.org.

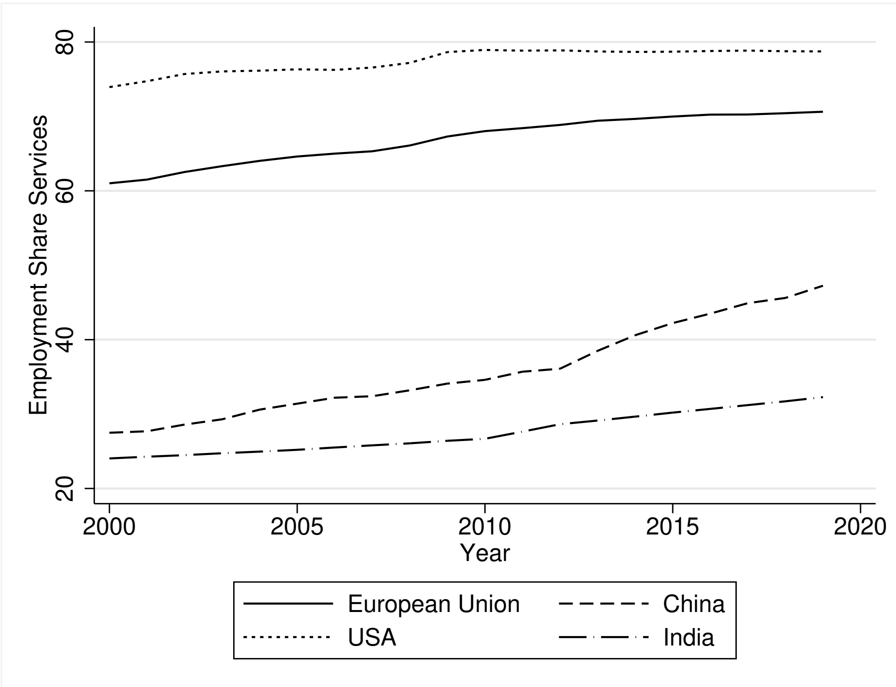

Figure 4.7: Employment Share Services by Country. Data Source: https://data.worldbank.org.

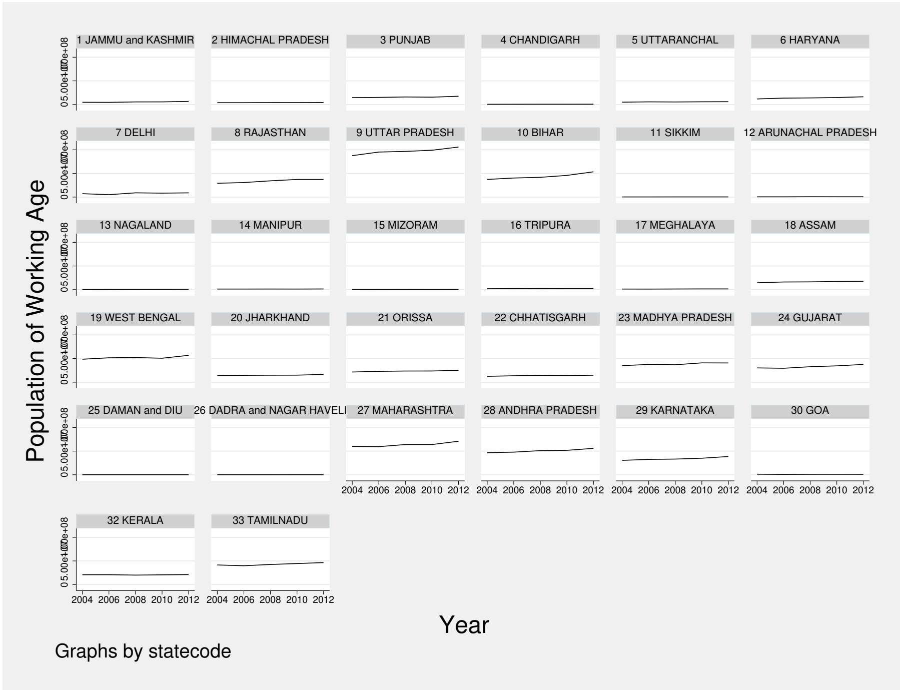

Figure 4.8: Population By State. Data Source: EUS by NSSO, Rounds 60 and 62-68.

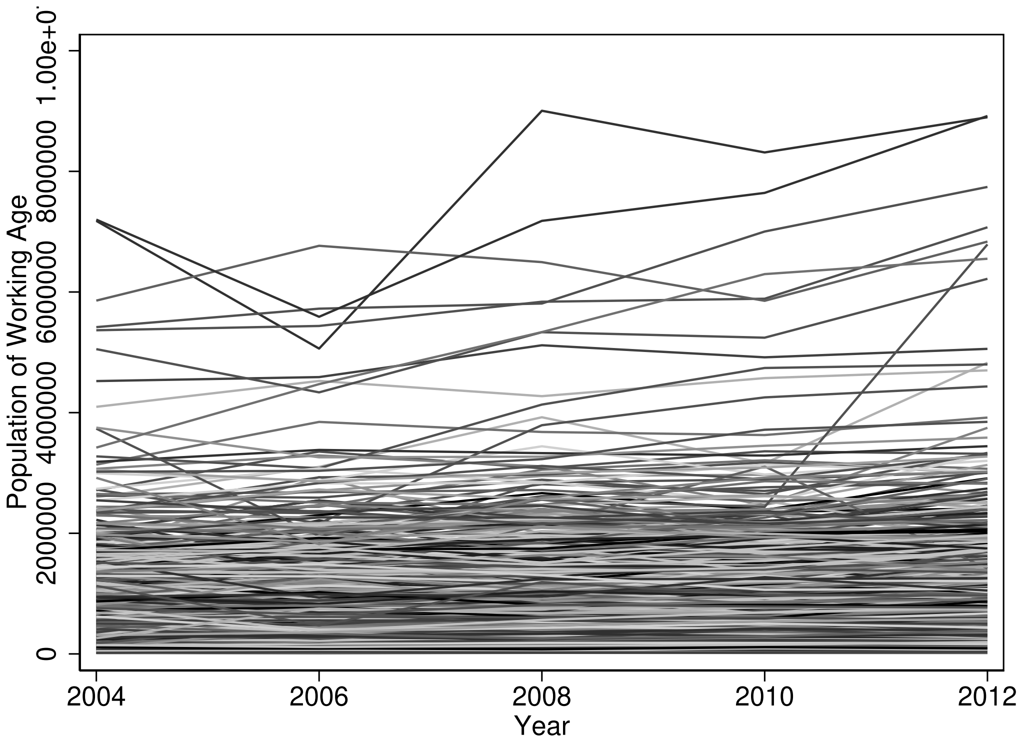

Figure 4.9: Population By District. Data Source: EUS by NSSO, Rounds 60 and 62-68.

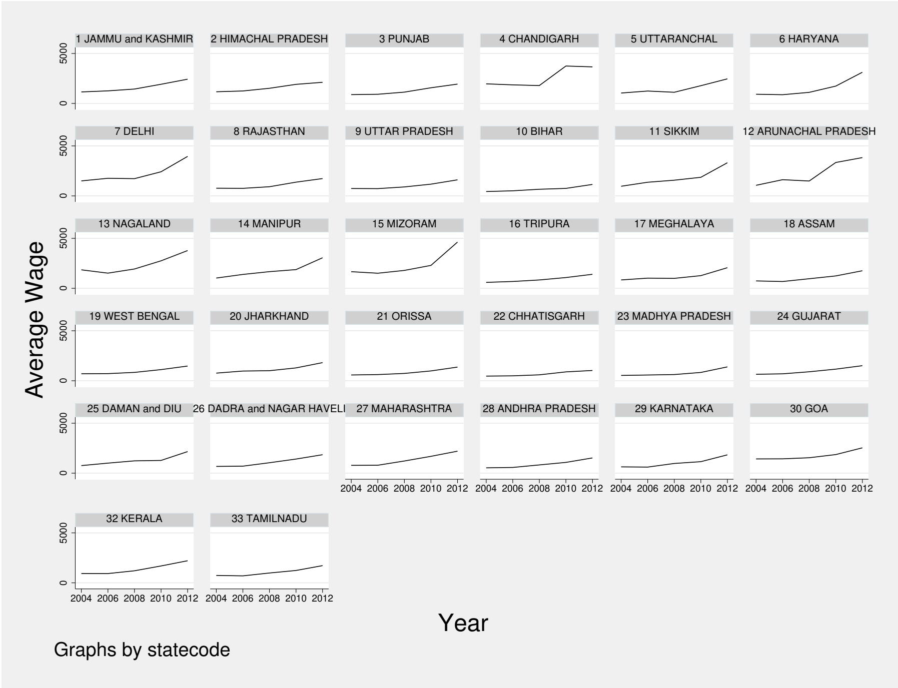

Figure 4.10: Average Wage by State. Data Source: EUS by NSSO, Rounds 60 and 62-68.

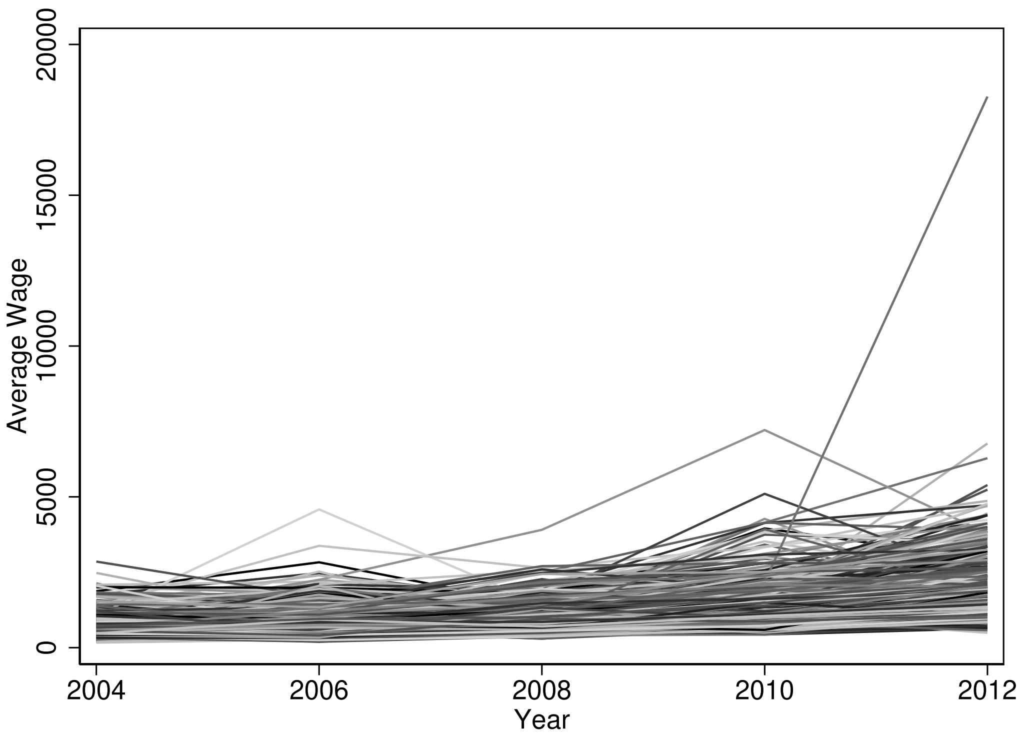

Figure 4.11: Average Wage by District. Data Source: EUS by NSSO, rounds 60 and 62-68.

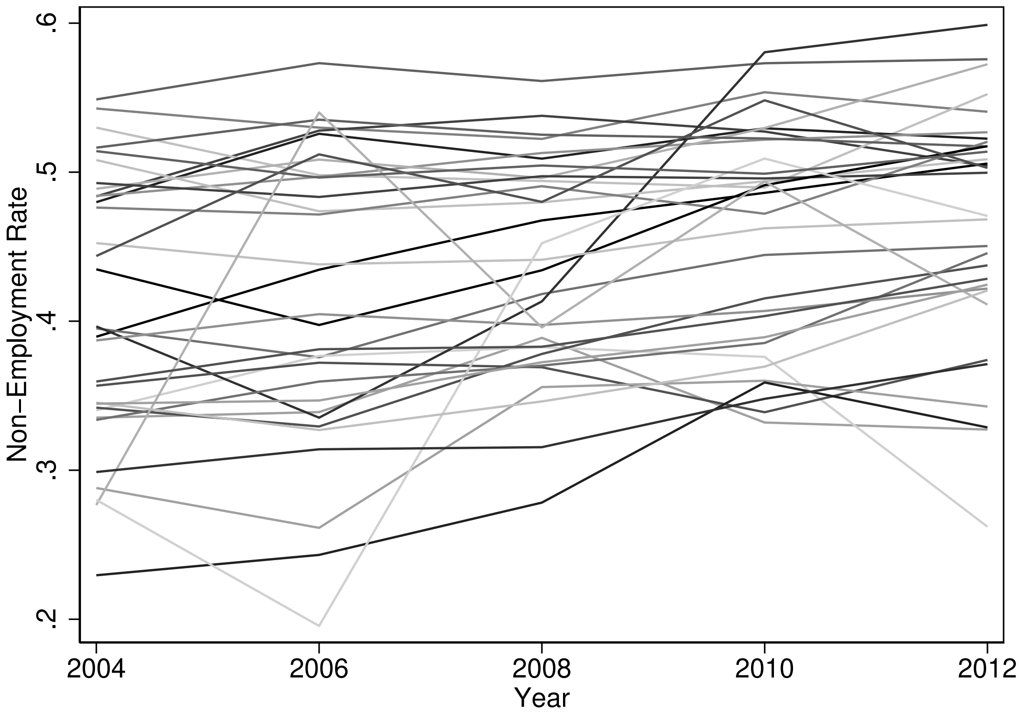

Figure 4.12: Non-Employment Rate by State. Data Source: EUS by NSSO, Rounds 60 and 62-68.

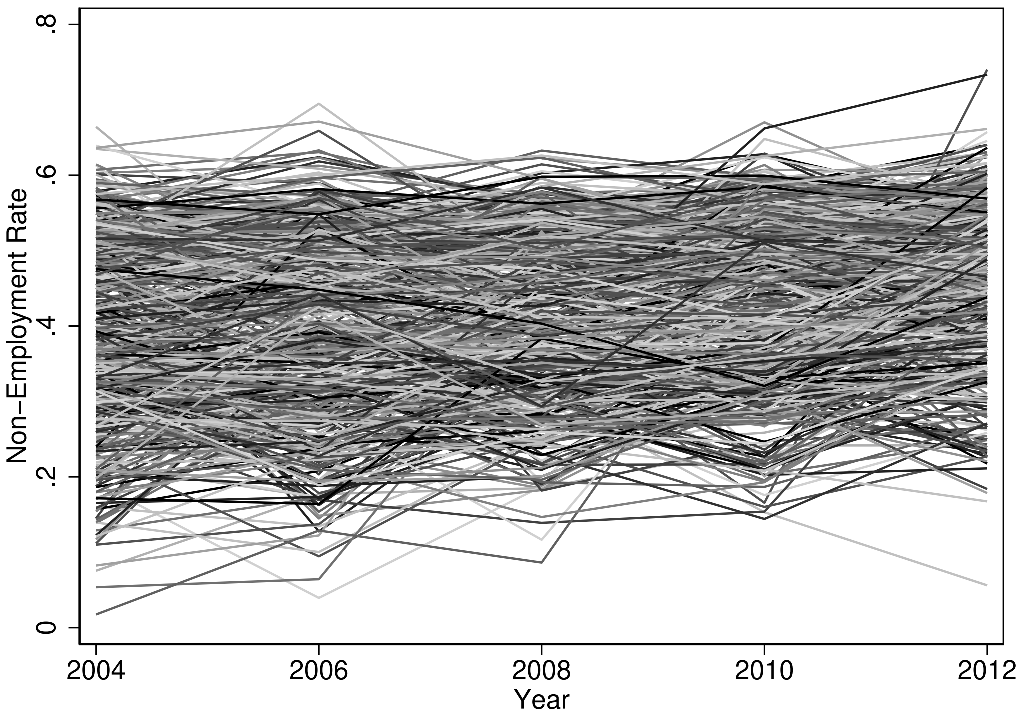

Figure 4.13: Non-Employment Rate by District. Data Source: EUS by NSSO, Rounds 60 and 62-68.

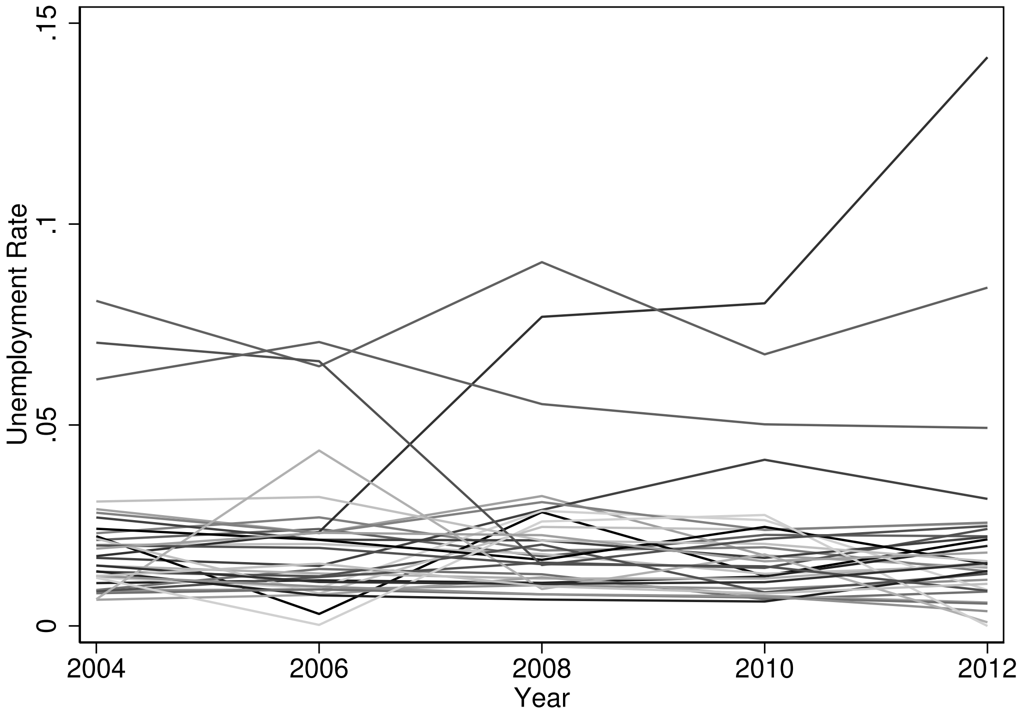

Figure 4.14: Unemployment Rate by State. Data Source: EUS by NSSO, Rounds 60 and 62-68.

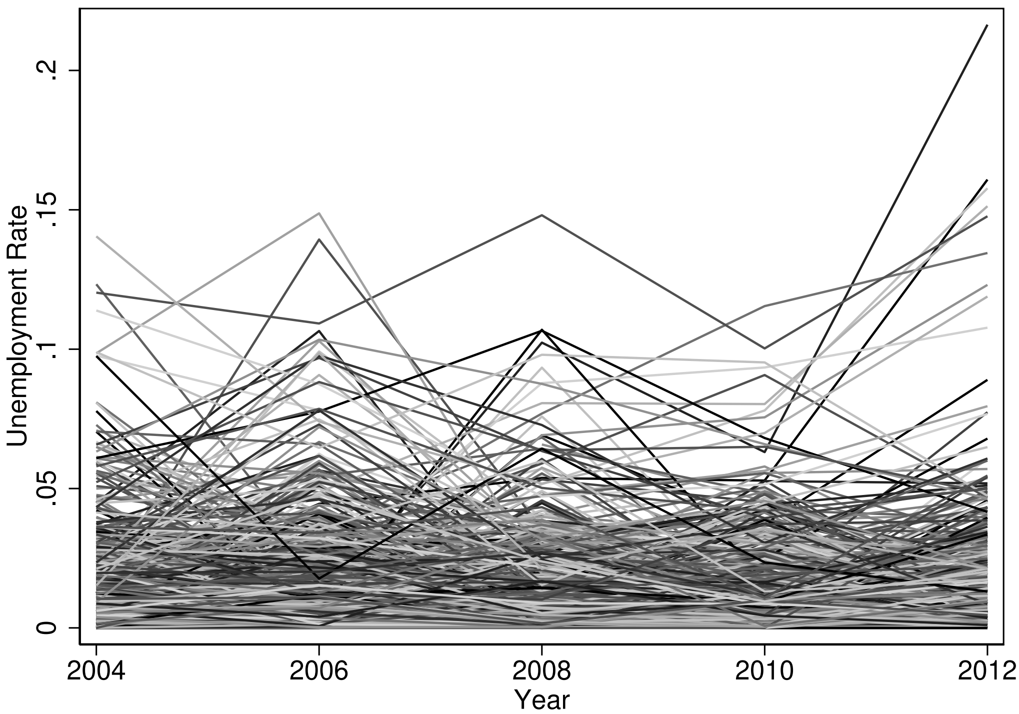

Figure 4.15: Unemployment Rate by District. Data Source: EUS by NSSO, Rounds 60 and 62-68.

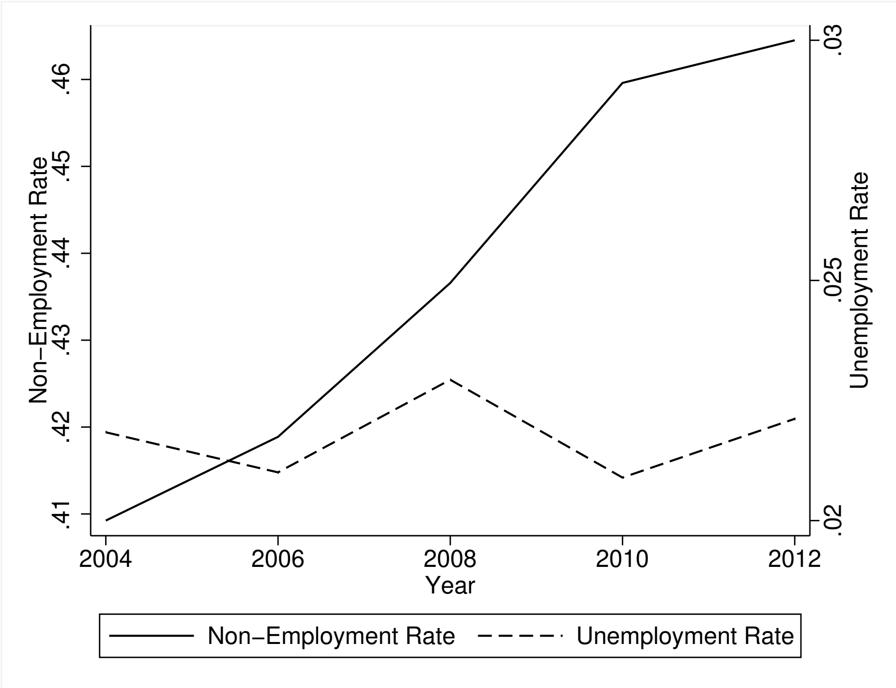

Figure 4.16: Unemployment Rate and Non-Employment Rate Averaged over States. Data Source: EUS by NSSO, Rounds 60 and 62-68.

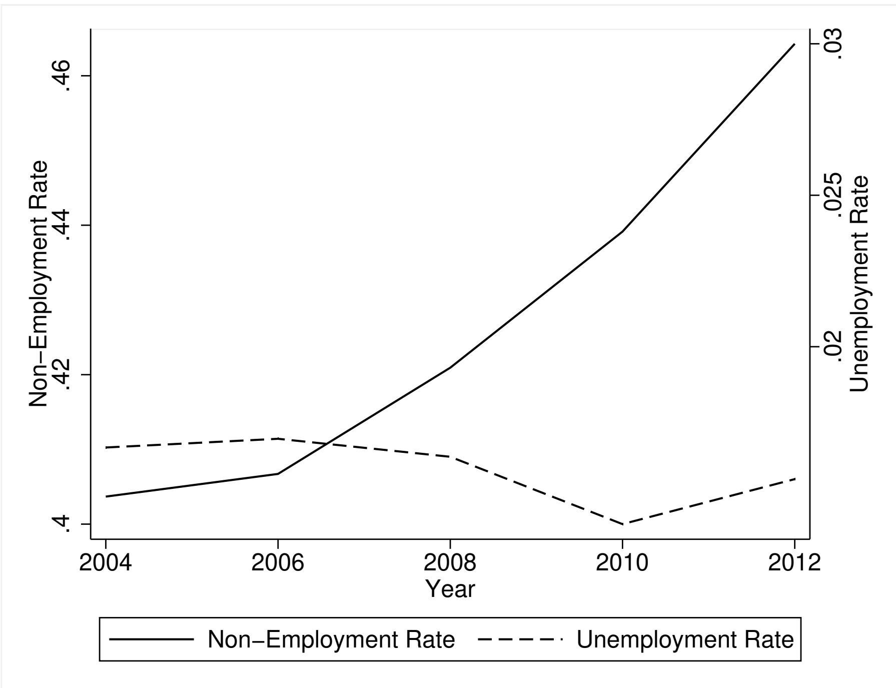

Figure 4.17: Unemployment Rate and Non-Employment Rate Averaged over Districts. Data Source: EUS by NSSO, Rounds 60 and 62-68.

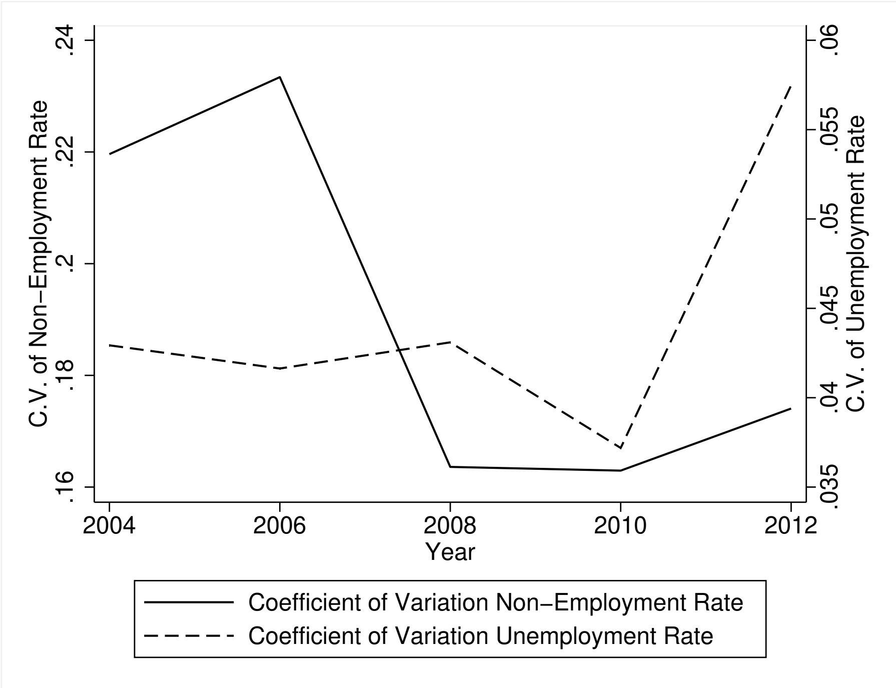

Figure 4.18: Coefficient of Variation of the Non-Employment and Unemployment Rates by States. Data Source: EUS by NSSO, Rounds 60 and 62-68.

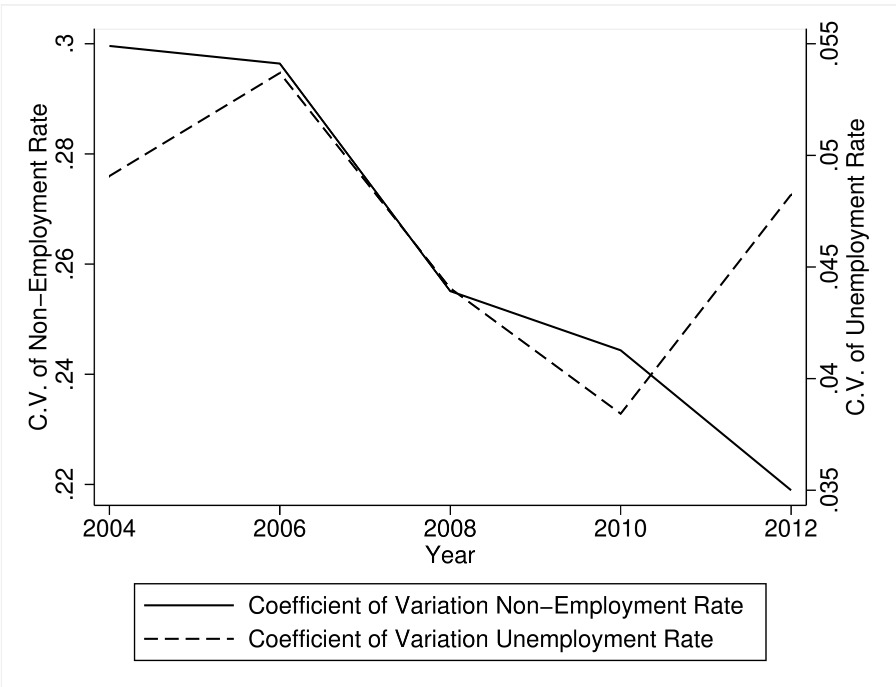

Figure 4.19: Coefficient of Variation of the Non-Employment and Unemployment Rates by Districts. Data Source: EUS by NSSO, Rounds 60 and 62-68.

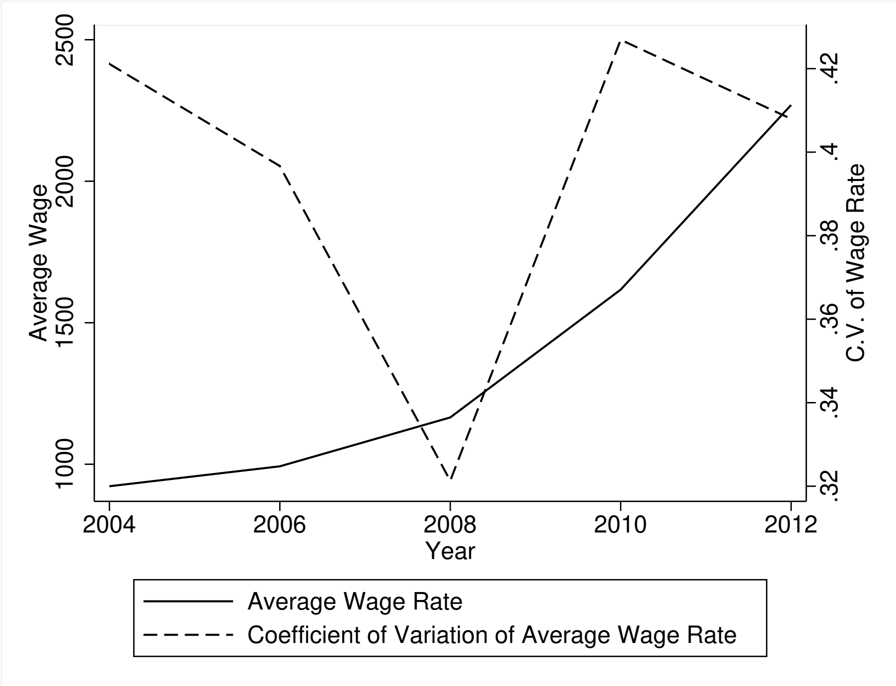

Figure 4.20: Average Wage and Coefficient of Variation of the Average Wage over States. Data Source: EUS by NSSO, Rounds 60 and 62-68.

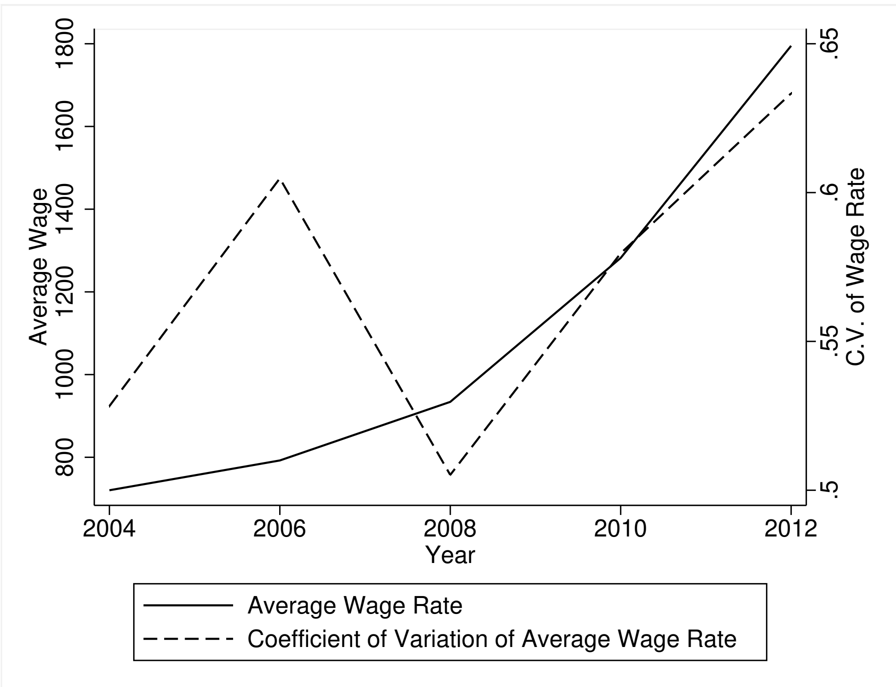

Figure 4.21: Average Wage and Coefficient of Variation of the Average Wage over Districts. Data Source: EUS by NSSO, Rounds 60 and 62-68.

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4 Bibliography

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Appendix A

Appendix to Chapter 2

A Appendix to Chapter 2

Table A.1: Confusion Matrix - Benchmarks

	Binary for working in FTC/PC		
Benchmark I, Cutoff = 0.5			
Predicted Value	0	1	Total
	No.	No.	No.
0	66,231	5,819	72,050
1	195	158	353
Total	66,426	5,977	72,403
Benchmark I, Cutoff = 0.25			
Predicted Value	0	1	Total
	No.	No.	No.
0	64,628	4,997	69,625
1	1,798	980	2,778
Total	66,426	5,977	72,403
Benchmark II, Cutoff = 0.5			
Predicted Value	0	1	Total
	No.	No.	No.
0	38,627	2,184	40,811
1	295	283	578
Total	38,922	2,467	41,389
Benchmark II, Cutoff = 0.25			
Predicted Value	0	1	Total
	No.	No.	No.
0	37,515	1,571	39,086
1	1,407	896	2,303
Total	38,922	2,467	41,389

Notes: Confusion matrices for benchmarks I and II with cut-off values 0.5 and 0.25. Data Source: soep.v35, 2019.

Table A.2: Confusion Matrix - LASSO

	Binary for working in FTC/PC		
Cutoff = 0.5			
Predicted Value	0	1	Total
	No.	No.	No.
0	28,334	1,442	29,776
1	406	675	1,081
Total	28,740	2,117	30,857
Cutoff = 0.25			
Predicted Value	0	1	Total
	No.	No.	No.
0	27,179	865	28,044
1	1,561	1,252	2,813
Total	28,740	2,117	30,857

Notes: Confusion matrices for LASSO with cut-off values 0.5 and 0.25. Data Source: soep.v35, 2019.

Table A.3: Confusion Matrix - Elastic Net

	Binary for working in FTC/PC		
Cutoff = 0.5			
Predicted Value	0	1	Total
	No.	No.	No.
0	28,342	1,447	29,789
1	398	670	1,068
Total	28,740	2,117	30,857
Cutoff = 0.25			
Predicted Value	0	1	Total
	No.	No.	No.
0	27,196	874	28,070
1	1,544	1,243	2,787
Total	28,740	2,117	30,857

Notes: Confusion matrices for Elastic Net with cut-off values 0.5 and 0.25. Data Source: soep.v35, 2019.

Table A.4: Comparison of Selected Variables LASSO and Elastic Net

Variable	LASSO	Elastic Net
Constant	-63.00259	-61.84654
Survey Year	-.0184599	-.023674
Personal Characteristics:		
Age	-.0081801	-.008492
Binary for Living in West Germany	-.0809619	-.0829995
Marital Status:		
Married	-.1386285	-.1352393
Married, separated	-.2121471	-.2094622
Single	.1867238	.1913846
Divorced	.0019445	.0096551
Partner Lives in HH	-.0467637	-.0487818
Employment Level Partner:		
Partner Employed FTC	.1359622	.139465
Partner Employed PC	-.1152335	-.1140843
Relation to HH Head:		
Child	.0061357	.0071235
Relative	-.5875952	-.5985335
Number of HH Members Age 0-14	-.0267813	-.027739
Number of HH Members Age 2-4	-.0426281	-.0445373
Number of HH Members Age 8-10	-.1279526	-.1291161
Number of HH Members Age 13-15	.0443675	.0466166
Disability Status of Individual	.0869584	.0898674
Number of Doctor Visits Last Three Mths.	.0038927	.0041092
Satisfaction with Health:		
Satisfied 7 of 10	.0225451	.0239976
Satisfied 0 of 10		-.0562119
Satisfied 2 of 10		.1088539
Satisfaction with Health:		
Very good	-.1456448	-.146237
Overall Live Satisfaction:		
Not Applicable	-.6618666	
Satisfied 3 of 10	.0739443	.0765171
Satisfied 1 of 10		-.5406347
Satisfied 9 of 10		-.1042566
Worried About Economic Development:		

To be continued

Table A.4 (continued)

Variable	LASSO	Elastic Net
Very Concerned	-.0401911	-.0410536
Somewhat Concerned	.0115864	.0125897
Worried About Finances:		
Somewhat Concerned	.0438268	.0440327
Not Concerned At All	-.1162175	-.1197126
Worried About Own Health:		
Very Concerned	-.184431	-.186451
Worried About Environment:		
Very Concerned	-.1196381	-.1204921
Worried About Peace:		
Not Concerned At All	.0547825	.0564328
Somewhat Concerned	-.0192767	-.0215403
Worried About Crime in Germany:		
Not Concerned At All	.1383208	.1378249
Worried About Job Security:		
Very Concerned	.7438182	.7440751
Not Concerned At All	-.6618186	-.6587449
Worried About Immigration to Germany:		
Somewhat Concerned	-.0074339	-.008819
Not Concerned At All	.178177	.1781137
Worried About Hostility to Foreigners:		
Somewhat Concerned	.0281526	.028416
Not Concerned At All	-.0029735	-.005749
Current Life Satisfaction:		
1 Satisfied: On Scale 0-Low to 10-High	-.5322256	
4 Satisfied: On Scale 0-Low to 10-High	-.2377346	-.2426721
6 Satisfied: On Scale 0-Low to 10-High	-.0186354	-.0205549
8 Satisfied: On Scale 0-Low to 10-High	.009391	.0105775
9 Satisfied: On Scale 0-Low to 10-High	-.1021068	
Current Life Satisfaction:		
0 Satisfied: On Scale 0-Low to 10-High		-.6735141
Satisfaction With Health:		
0 Satisfied: On Scale 0-Low to 10-High	-.0431737	
2 Satisfied: On Scale 0-Low to 10-High	.1062928	
3 Satisfied: On Scale 0-Low to 10-High	.0827823	.0847109
7 Satisfied: On Scale 0-Low to 10-High	-.0134761	-.0163252

To be continued

Table A.4 (continued)

Variable	LASSO	Elastic Net
10 Satisfied: On Scale 0-Low to 10-High	.1807027	.1824463
1 Satisfied: On Scale 0-Low to 10-High	.1430209	.1500169
2 Satisfied: On Scale 0-Low to 10-High	-.0092035	-.013537
5 Satisfied: On Scale 0-Low to 10-High	-.0074814	-.0092383
6 Satisfied: On Scale 0-Low to 10-High	.0513218	.0531249
7 Satisfied: On Scale 0-Low to 10-High	-.0227999	-.0237187
9 Satisfied: On Scale 0-Low to 10-High	.1185001	.1206168
10 Satisfied: On Scale 0-Low to 10-High	.0931925	.096138
4 Satisfied: On Scale 0-Low to 10-High	.1455746	.1478298
5 Satisfied: On Scale 0-Low to 10-High	.0100302	.0118162
7 Satisfied: On Scale 0-Low to 10-High	-.0536664	-.0554295
8 Satisfied: On Scale 0-Low to 10-High	-.0860925	-.086752
Satisfaction With Amount of Leisure Time:		
0 Satisfied: On Scale 0-Low to 10-High	-.7456158	-.7525537
3 Satisfied: On Scale 0-Low to 10-High	.1086804	.1108154
8 Satisfied: On Scale 0-Low to 10-High	-.0624292	-.0638735
10 Satisfied: On Scale 0-Low to 10-High	.0682619	.0686774
4 Satisfied: On Scale 0-Low to 10-High		.0002016
Homework Hours Workday	-.0016402	-.0024305
Hours Weekdays Care For Persons	.0216233	.0224716
Education and Training, Learning Hrs, Workg. (Employed)	.0457432	.0469743
Repairs etc. Hrs, Workg.	-.0120846	-.0132193
Party Preference Intensity:		
Quite Interested	.0439613	.0456677
Employment Characteristics:		
Employment Status:		
Full-Time Employment	-.1986784	-.2043818
Labour Force Status:		
Working	.1886847	.0972424
Working But NW Past 7 Days		-.0971034
Employed by Emp. Agency:		
Yes	1.175922	.5901184
No		-.590021
Public Service	-.7339684	-.7270048
Is Industrial Sector Worker:		

To be continued

Table A.4 (continued)

Variable	LASSO	Elastic Net
Untrained Blue-Collar Worker	-.0187045	-.020963
Semi-Trained Blue-Collar Worker	.1400324	.1416963
Is Civil Servant:		
Not Applicable	.4395662	.4306596
Low-Level Civil Service	-.5064965	-.5042139
High-Level Civil Service	-.5218965	-.5352524
Executive Level Civil Service	-.3575453	-.3835201
University Education Completed	-.1191976	-.1239132
Required Training:		
No Training	.3400002	.3444311
Courses	.1562233	.1568099
Vocational Training	-.1062939	-.1079449
University since 99	.3281191	.3322123
Working in Occ Trained for:		
No	.1845213	.1852929
In Training	1.429054	1.436907
Number of Workers:		
Lt 5	-.7589456	-.7571098
Ge 5 Lt 10	-.3459329	-.3456702
Ge 11 Lt 20	-.2478702	-.2477825
91-04: Ge 5 Lt 20	-.3675041	-.3667933
Ge 100 Lt 200	.0056255	.0095761
Ge 200 Lt 2000	.1848989	.1863691
Ge 2000	.1485518	.150697
Occupation:		
Soldiers	4.458527	4.421083
Corporate Managers	-.2395666	-.2452781
Managers of Small Enterprises	.0184578	.0289969
Physical, Mathematical and Engineers	-.0471944	-.0502541
Life Science and Health Professionals	1.838288	1.834819
Teaching Professionals	.4853009	.4877683
Other Professionals	.2092097	.2076738
Teaching Associate Professionals	.3303451	.3313095
Models, Salespersons and Demonstrators	.0728852	.0771956
Skilled Agricultural and Fishery Worker	1.140985	1.140092
Metal, Machinery and Related Trades Workers	.1701356	.1744844

To be continued

Table A.4 (continued)

Variable	LASSO	Elastic Net
Other Craft and Related Trades Workers	.2505166	.2569299
Stationary Plant and Related Operators	-.0067208	-.0204409
Machine Operators and Assemblers	-.0690001	-.070593
Drivers and Mobile Plant Operators	-.125837	-.1271075
Sales and Services Elementary Occupation	-.3884037	-.389018
Agricultural, Fishery and Related Labourers	2.072812	2.071354
Labourers in Mining, Construction, Manufacturing	.2210282	.2227479
Life Science and Health Associate Professionals		-.0038369
Industry Occupation [pbra] (NACE Rev. 1.1, Sector)	.0048459	.0047395
Employed by Current Employer	.049683	.0547276
Length Of Time With Firm	-.1237557	-.1152371
Actual Work Time Per Week		
Actual Working Time with Overtime Hours/Week.	.0037568	.003912
Mini-/Midi Job:		
Yes, Mini-Job (up to 450 Euros)	-.0708877	-.0699421
Employment History:		
Annual Working Hours Last Year	-.0001938	-.0001947
Working Experience Part-Time Employment	-.0063979	-.0067715
Unemployment Experience	.0597071	.060557
Binary Variable, Employment Status Last Year	-.0036367	-.0613528
Employment Level Last Year:		
Full Time	-.0520134	-.0550004
Not working	.1189351	.0625709
2 Digit Industry Code:		
Energy,Water	-.1477462	-.1540087
Mining	1.126578	1.130565
Synthetics	-.446193	-.4579034
Iron, Steel	-.0071891	-.013827
Mechanical Eng	.0016068	.0057943
Wood, Paper, Print	-.0202246	-.0297967
Clothing,Text	.2440999	.246372
Food Industry	.1036659	.1026831
Construction	-.2160661	-.2160453
Constr. Relate	-.0749975	-.0806943
Other Trans.	-.376495	-.3751825

To be continued

Table A.4 (continued)

Variable	LASSO	Elastic Net
Financial Inst	-.4682907	-.4738068
Service Indust	.1236707	.12985
Trash Removal	-.3239809	-.3277415
Educ., Sport	.8534087	.8611568
Health Service	.0551587	.0651526
Other Services	-.0594344	-.0585401
Volunt., Church	.2994449	.3120191
Public Administration	.001077	.0139997
Maternity Protection or Parental Leave:		
Yes, Maternity Protection	-.5394411	-.5593322
New Work Since Last Year:		
No New Work	-.404218	
Change of Job Prev. Year:		
Yes	.7071265	.6949222
Occupational Change:		
Employed No Change	-.0586025	-.0644715
Employed No Info If Change	.3369624	.3428908
Reason for Occ. Change:		
Not Applicable	-.0819511	-.0428067
Terminated by employer		.042522
Returned to Past Employer After Break	.2356083	.2434905
New Position Different Employer	.3404714	.3493766
Taken On By Company	.4053407	.4041777
Changed Position Within Company	-.1812995	-.1892543
Nature of the Professional Change:		
Not Applicable		-.42246
Yes, I already have a new employment contract	-.0219686	-.0303981
No, nothing yet	.2162438	.2136977
I have not looked for a new job	-.0847005	-.0987163
Learned From Job Through	-.0113418	-.0114733
Actively Sought This Position	-.0774655	-.0820888
Education Charachteristics:		
School Leaving Degree:		
Intermediate School Degree	-.0184629	-.019986
Upper Secondary Degree	.0332286	.0362336

To be continued

Table A.4 (continued)

Variable	LASSO	Elastic Net
Dropout, No School Degree	.3254993	.330836
Vocational Degree Received East Germany:		
Not Applicable	.0326963	.0380116
Master Craftsman	-.0547595	-.0622137
Engineering, Technical Degree	.0489332	.0731482
School-Leaving Degree Outside Germany:		
Not Applicable	.0348645	.0356169
School, With Degree	-.0858982	-.0894528
Vocational Degree Received:		
Not Applicable	.3035058	.3064916
Vocational School	.0252325	.0270378
Health Care School	-.1574189	-.1629304
College Degree:		
University (East)	-.285738	-.3009206
Graduation, State Doctorate	.600347	.6058823
No Vocational Degree:		
Not Applicable	.2022526	.104408
No Vocation Degree		-.1043663
Type of tertiary degree	-.0079194	-.0081769
Apprenticeship	.5437866	.5409272
School Of Health Care	.3323939	.3366338
Civil Service Training	-.7368031	-.751933
Company Retraining	.3791216	.3866706
Other Training	.1129635	.1166614
Completed Education,Training After 2006	-.1590744	-.1598499
Other Income Components This Year:		
Unemployment Benefit	.0000366	.0000368
Maternity Benefit	-.0000211	-.0000228
Alimony	.0000485	.0000489
Housing Benefit	-.0000225	-.000024
Statutory Accident Insurance		3.62e-06
Losses From Capital Investment	.0000201	.0000204
Commuting, Travel Grant	-.0001091	-.0001139
Unemployment Benefit II	.0000302	.0000301
Divorce Alimony, During Separation	.0000701	.0000723

To be continued

Table A.4 (continued)

Variable	LASSO	Elastic Net
Severance Payment Amount	.0000107	.0000111

Note: Coefficients of LASSO and Elastic Net regressions, dependent variable is a binary variable for FTC/PC. Data Source: soep.v35, 2019.

Table A.5: Comparison of Selected Variables LASSO and Adaptive LASSO

Variable	LASSO	Adaptive LASSO
Marital Status:		
Married	-.1386285	-.2208794
Married, separated	-.2121471	-.3000315
Single	.1867238	.1828752
Divorced	.0019445	
Relation to HH Head:		
Child	.0061357	
Relative	-.5875952	-.7459194
Satisfaction with Health:		
Satisfied 7 of 10	.0225451	
Satisfied 2 of 10		.1126155
Overall Live Satisfaction:		
Not Applicable	-.6618666	-.8110444
Satisfied 3 of 10	.0739443	
Satisfied 1 of 10		-.6874382
Worried About Economic Development:		
Very Concerned	-.0401911	-.0624959
Somewhat Concerned	.0115864	
Worried About Crime in Germany:		
Somewhat Concerned	-.0192767	
Not Concerned At All	.1383208	.1727761
Worried About Immigration to Germany:		
Somewhat Concerned	-.0074339	
Not Concerned At All	.178177	.2109755
Worried About Hostility to Foreigners:		
Somewhat Concerned	.0281526	.0110409
Not Concerned At All	-.0029735	
Current Life Satisfaction:		
1 Satisfied: On Scale 0-Low to 10-High	-.5322256	
4 Satisfied: On Scale 0-Low to 10-High	-.2377346	-.311958
6 Satisfied: On Scale 0-Low to 10-High	-.0186354	
8 Satisfied: On Scale 0-Low to 10-High	.009391	
9 Satisfied: On Scale 0-Low to 10-High	-.1021068	-.1407916
Satisfaction With Health:		

To be continued

Table A.5 (continued)

Variable	LASSO	Adaptive LASSO
0 Satisfied: On Scale 0-Low to 10-High	-.0431737	
2 Satisfied: On Scale 0-Low to 10-High	.1062928	
3 Satisfied: On Scale 0-Low to 10-High	.0827823	.0714016
7 Satisfied: On Scale 0-Low to 10-High	-.0134761	
10 Satisfied: On Scale 0-Low to 10-High	.1807027	.2210018
Satisfaction With HH income:		
1 Satisfied: On Scale 0-Low to 10-High	.1430209	.0574196
2 Satisfied: On Scale 0-Low to 10-High	-.0092035	
5 Satisfied: On Scale 0-Low to 10-High	-.0074814	
6 Satisfied: On Scale 0-Low to 10-High	.0513218	.0571317
7 Satisfied: On Scale 0-Low to 10-High	-.0227999	
9 Satisfied: On Scale 0-Low to 10-High	.1185001	.1855502
10 Satisfied: On Scale 0-Low to 10-High	.0931925	.1539722
Satisfaction With Dwelling:		
4 Satisfied: On Scale 0-Low to 10-High	.1455746	.137073
5 Satisfied: On Scale 0-Low to 10-High	.0100302	
7 Satisfied: On Scale 0-Low to 10-High	-.0536664	-.0677229
8 Satisfied: On Scale 0-Low to 10-High	-.0860925	-.1112156
Homework Hrs., Workg.		
Repairs etc. Hrs, Workg.	-.0120846	
Labour Force Status:		
Working	.1886847	
Is Industrial Sector Worker:		
Untrained Blue-Collar Worker	-.0187045	
Semi-Trained Blue-Collar Worker	.1400324	.1656729
Number of Workers:		
Lt 5	-.7589456	-.8853994
Ge 5 Lt 10	-.3459329	-.4215242
Ge 11 Lt 20	-.2478702	-.3090105
91-04: Ge 5 Lt 20	-.3675041	-.4882508
Ge 100 Lt 200	.0056255	
Ge 200 Lt 2000	.1848989	.2294903
Ge 2000	.1485518	.198423
Occupation:		
Soldiers	4.458527	4.818741

To be continued

Table A.5 (continued)

Variable	LASSO	Adaptive LASSO
Corporate Managers	-.2395666	-.2997571
Managers of Small Enterprises	.0184578	
Physical, Mathematical and Engineers	-.0471944	
Life Science and Health Professionals	1.838288	1.92661
Teaching Professionals	.4853009	.6752756
Other Professionals	.2092097	.2764768
Teaching Associate Professionals	.3303451	.4072586
Models, Salespersons and Demonstrators	.0728852	.0484706
Skilled Agricultural and Fishery Worker	1.140985	1.388351
Metal, Machinery and Related Trades Workers	.1701356	.2848235
Other Craft and Related Trades Workers	.2505166	.3795969
Stationary Plant and Related Operators	-.0067208	
Machine Operators and Assemblers	-.0690001	
Drivers and Mobile Plant Operators	-.125837	-.1502942
Sales and Services Elementary Occupation	-.3884037	-.5073173
Agricultural, Fishery and Related Labourers	2.072812	2.501904
Labourers in Mining, Construction, Manufacturing	.2210282	.2594937
Actual Work Time Per Week		
Actual Working Time With Overtime Hours/Week.	.0037568	.0132946
Mini-/Midi Job:		
Yes, Mini-Job (up to 450 Euros)	-.0708877	
Binary Variable, Employment Status Last Year	-.0036367	
Employment Level Last Year:		
Full Time	-.0520134	
Not working	.1189351	
2 Digit Industry Code:		
Energy, Water	-.1477462	-.1511243
Mining	1.126578	1.508073
Synthetics	-.446193	-.6727912
Iron, Steel	-.0071891	
Mechanical Eng	.0016068	
Wood, Paper, Print	-.0202246	
Clothing, Text	.2440999	.2773397
Food Industry	.1036659	.1087365
Construction	-.2160661	-.2466565

To be continued

Table A.5 (continued)

Variable	LASSO	Adaptive LASSO
Constr. Relate	-.0749975	-.0738046
Other Trans.	-.376495	-.506295
Financial Inst	-.4682907	-.7129727
Service Indust	.1236707	.1221134
Trash Removal	-.3239809	-.3261014
Educ., Sport	.8534087	.8529617
Health Service	.0551587	
Other Services	-.0594344	-.0265848
Volunt., Church	.2994449	.3006229
Public Administration	.001077	
No New Work	-.404218	
Change of Job in Prev. Year:		
Yes	.7071265	.7627699
Occupational Change:		
Employed No Change	-.0586025	
Employed No Info If Change	.3369624	.2773757
Reason for Occ. Change:		
Not Applicable	-.0819511	
Nature of Professional Change:		
Returned to Past Employer After Break	.2356083	.2618492
New Position Different Employer	.3404714	.4156864
Taken On By Company	.4053407	.5307521
Changed Position Within Company	-.1812995	
No Change		-.4761477
Perspective at the End of Employment Relationship:		
Yes, I already have a new employment contract	-.0219686	
No, nothing yet	.2162438	.2561616
I have not looked for a new job	-.0847005	
School Leaving Degree:		
Intermediate School Degree	-.0184629	
Upper Secondary Degree	.0332286	
Dropout, No School Degree	.3254993	.4006688
Vocational Degree Received East Germany:		
Not Applicable	.0326963	.0035241
Master Craftsman	-.0547595	

To be continued

Table A.5 (continued)

Variable	LASSO	Adaptive LASSO
Engineering, Technical Degree	.0489332	
School-Leaving Degree Outside Germany:		
Not Applicable	.0348645	
School, With Degree	-.0858982	-.0387005
Vocational Degree Received:		
Not Applicable	.3035058	.4367867
Vocational School	.0252325	
Health Care School	-.1574189	-.1883394
Apprenticeship	.5437866	.490996
School Of Health Care	.3323939	.1683506
Civil Service Training	-.7368031	-.5909423
Company Retraining	.3791216	.1317207
Other Training	.1129635	
Maternity Benefit	-.0000211	
Housing Benefit	-.0000225	
Severance Payment Amount	.0000107	
Indemnity		5.96e-06

Note: Coefficients of LASSO and Adaptive LASSO regressions, dependent variable is a binary variable for FTC/PC. Data Source: soep.v35, 2019.

Table A.6: Comparison of Selected Variables LASSO by Gender

Variable	Men	Women
Constant	-58.72327	-80.47422
Survey Year		
Personal Characteristics:		
Age		-.0087634
Binary for Living in West Germany	-.3011349	
Marital Status:		
Married, separated	-.082663	-.1199978
Single	.1658143	.2204063
Divorced	.0202017	
Married		-.1373747
Partner Lives In Household	-.0970071	
Employment Level Partner:		
Partner employed FTC	.3259667	
Partner Employed PC	-.1903759	-.0208529
Relation to HH Head:		
Head	-.1308536	
Child	.080226	
Relative	-2.335022	
Number of HH Members Age 0-1	.0557527	
Number of HH Members Age 5-7	-.0713392	.0090983
Number of HH Members Age 0-14	-.1046483	
Number of HH Members Age 2-4		
Number of HH Members Age 8-10	-.0815375	-.0379201
Number of HH Members Age 13-15		.0577875
Current Health:		
Poor	-.0076284	
Satisfaction with Health, Var 0:		
9 Satisfied: On Scale 0-Low to 10-High	-.0942016	
0 Satisfied: On Scale 0-Low to 10-High		-.0687362
Satisfaction with Health, Var1:		
Satisfied 1 of 10	-.3898868	
Satisfaction with Health:		
Satisfied 2 of 10	.1624874	
Satisfaction with Health, Var1:		
Satisfied 7 of 10	.0190689	

To be continued

Table A.6 (continued)

Variable	Men	Women
Satisfied 10 of 10	-.1522875	
Satisfaction with Health, Var2:		
Medium	.008186	
Very good		-.1698197
Worried about Economic Development:		
Somewhat Concerned	.0056813	
Worried about Economic Development:		
Very Concerned		-.0067098
Somewhat Concerned	.0805849	
Not Concerned At All	-.197901	
Worried about Own Health:		
Very Concerned		-.2862861
Worried about Environment:		
Very Concerned	-.0585852	-.0737796
Not Concerned At All	.086689	
Somewhat Concerned		.0180229
Worried about Peace:		
Somewhat Concerned	-.0448221	
Not Concerned At All	.0728566	
Worried about Peace:		
Very Concerned		-.0120864
Not Concerned At All	.1923234	.0417426
Worried about Job Security:		
Very Concerned	.6008341	.7901629
Not Concerned At All	-.4796357	-.7334652
Worried about Immigration to Germany:		
Not Concerned At All	.0854173	.1845053
Worried about Hostility to Foreigners:		
Very Concerned	.0210068	-.060843
Not Concerned At All	-.06452	
Current Life Satisfaction:		
4 Satisfied: On Scale 0-Low to 10-High	-.1114353	-.0643965
5 Satisfied: On Scale 0-Low to 10-High	.1412427	
10 Satisfied: On Scale 0-Low to 10-High	.2525636	
Current Life Satisfaction:		
1 Satisfied: On Scale 0-Low to 10-High		-.0256045

To be continued

Table A.6 (continued)

Variable	Men	Women
Overall Life Satisfaction:		
Satisfied 1 of 10	-.5248566	
Satisfied 2 of 10	-.2265687	
Satisfied 3 of 10	.2024166	
Satisfied 9 of 10	-.1005691	
Overall Life Satisfaction: Not Applicable		-.8485106
Satisfied 8 of 10		.0616197
Satisfied 10 of 10		-.0916268
Satisfaction with Work:		
2 Satisfied: On Scale 0-Low to 10-High	-.0914022	
3 Satisfied: On Scale 0-Low to 10-High	.0782658	
8 Satisfied: On Scale 0-Low to 10-High	-.0172663	
9 Satisfied: On Scale 0-Low to 10-High	-.0173703	
10 Satisfied: On Scale 0-Low to 10-High	.231448	.0266986
7 Satisfied: On Scale 0-Low to 10-High		-.0701565
Satisfaction with HH income:		
2 Satisfied: On Scale 0-Low to 10-High	-.0319486	
3 Satisfied: On Scale 0-Low to 10-High	.1927305	-.077593
4 Satisfied: On Scale 0-Low to 10-High	-.0935371	
5 Satisfied: On Scale 0-Low to 10-High	.0067511	-.034334
8 Satisfied: On Scale 0-Low to 10-High	-.0443234	
10 Satisfied: On Scale 0-Low to 10-High	.1454057	
Satisfaction with HH income:		
1 Satisfied: On Scale 0-Low to 10-High		.1901658
6 Satisfied: On Scale 0-Low to 10-High		.0291393
7 Satisfied: On Scale 0-Low to 10-High		-.027964
9 Satisfied: On Scale 0-Low to 10-High		.0565528
Satisfaction with Dwelling:		
0 Satisfied: On Scale 0-Low to 10-High	.9453672	
1 Satisfied: On Scale 0-Low to 10-High	.2069447	
4 Satisfied: On Scale 0-Low to 10-High	.288672	.0227432
5 Satisfied: On Scale 0-Low to 10-High	.0346051	
7 Satisfied: On Scale 0-Low to 10-High	-.0478856	
8 Satisfied: On Scale 0-Low to 10-High	-.0177693	-.0607876
Satisfaction with Amount of Leisure Time:		
0 Satisfied: On Scale 0-Low to 10-High	-1.784953	

To be continued

Table A.6 (continued)

Variable	Men	Women
3 Satisfied: On Scale 0-Low to 10-High	.1196927	
6 Satisfied: On Scale 0-Low to 10-High	-.0328879	
7 Satisfied: On Scale 0-Low to 10-High	-.0507106	
8 Satisfied: On Scale 0-Low to 10-High	-.0796446	-.0095532
9 Satisfied: On Scale 0-Low to 10-High	.0758454	-.0168515
10 Satisfied: On Scale 0-Low to 10-High	.1139371	
1 Satisfied: On Scale 0-Low to 10-High		.0226822
Housework Difficult Alone	.807157	
Interest in Politics:		
Not Much	.0516053	-.0464954
Very Strong		.073207
Strong		.0146208
Party Preference Intensity:		
Quite interested	.1125424	
Moderate	-.0792618	
Weakly	-.248889	
Very Seriously		-.0827588
Legally Handicapped, Reduced Employment		-.0301668
Childcare Hours	-.0247656	
Hours Weekday Leisure, Hobbies	.0220412	
Hours Weekdays Care For Persons	.0757554	.0060507
Education and Training, Learning HRS., WORKG. (Employed)		.1003165
Repairs etc. HRS., WORKG.		-.0715957
Employment Characteristics:		
Employment Status:		
Full-Time Employment	-.5867021	
Marginal, Irregular Part-Time Employment	.5848257	
Regular Part-Time Employment		.0026821
Labour Force Status:		
Working		.4459699
Employed by Emp. Agency:		
Yes	.971461	1.350565
Binary for: Is in Public Service	-.9189487	-.5791184
Level Civil Service:		
Not Applicable	.3152564	.4493711

To be continued

Table A.6 (continued)

Variable	Men	Women
Low-Level Civil Service	-.5203218	
High-Level Civil Service	-.0481565	-.6534005
Executive Level Civil Service		-1.000658
Is Industrial Sector Worker:		
Untrained Blue-Collar Worker	-.08398	
Semi-Trained Blue-Collar Worker	.1402854	.0198734
Foreman		.0014518
Required Training, Var 1:		
Professional Training Completed	.1254699	
Higher Education (University of Applied Science):		
Completed		.1892053
Required Training, Var 2:		
No Training	.3818036	.0575368
Intro. to Job	.002599	
Courses	.0051371	.0263202
Vocational Training	-.4015793	-.0180182
Technical College since 99	-.2840916	
University since 99	.2414156	.1744055
Desired Weekly Working Hours	.0133147	
Working in Occ. Trained for:		
In Training	1.736125	1.508618
No		.296384
Overtime Last Month	-.0439599	
Number of Workers:		
Lt 5	-.8354941	-.6866999
Ge 5 Lt 10	-.3240539	-.3102097
Ge 11 Lt 20	-.1488045	-.2090981
91-04: Ge 5 Lt 20	-.5657856	-.1234681
Ge 100 Lt 200	-.1122326	.1461371
Ge 200 Lt 2000	.0460363	.2723408
Ge 2000	.1538729	.0327218
Occupation:		
Soldiers	3.977911	1.429099
Legislators and Senior Officials	.0884156	
Managers of Small Enterprises	.6552876	-.0771435
Physical, Mathematical and Engineers	-.1865668	.0691561

To be continued

Table A.6 (continued)

Variable	Men	Women
Life Science and Health Professionals	1.719558	1.645521
Teaching Professionals	.0916279	.5960729
Physical and Engineering Science Associate Professionals	-.0826693	
Life Science and Health Associate Professionals	-.777646	
Teaching Associate Professionals	.7685305	.1262686
Office Clerks	.143026	-.0172441
Skilled Agricultural and Fishery Worker	.6771377	1.093147
Metal, Machinery and Related Trades Workers	.1381075	-.091105
Other Craft and Related Trades Workers	.1205818	.1207622
Stationary Plant and Related Operators	-.2957336	.0475114
Machine Operators and Assemblers	-.3427075	
Drivers and Mobile Plant Operators	-.1762684	-.4242938
Sales and Services Elementary Occupation	-.4990551	-.1737874
Agricultural, Fishery and Related Labourers	1.270518	1.873253
Labourers in Mining, Construction, Manufacturing	.2140928	
Corporate Managers		-.7281644
Other Professionals		.2297964
Models, Salespersons and Demonstrators		.0081665
Precision, Handicraft, Craft Printing		-.1351541
Industry Occupation	.0040719	.0007048
Employed by Current Employer	.0295796	.0401449
Length Of Time With Firm	-.1112361	-.151783
Actual Work Time Per Week		
Mini-/Midi Job:		
Yes, Mini-Job (up to 450 Euros)	-.9660839	
Yes, Midi-Job (450 to 850 euros)	-2.090552	
Current Occupational Classification	-.0000105	
Last Reached SIOPS Score	.0037669	
Employment History:		
Annual Working Hours Last Year	-.0001783	-.0000773
Working Experience Full-Time	-.0050361	-.0074318
Unemployment Experience	.0795334	.0260584
Binary Variable, Employment Status Last Year	-.001196	
Employment Level Last Year:		
Full Time	-.1307926	-.0610833

To be continued

Table A.6 (continued)

Variable	Men	Women
Not working	.4908481	
2 Digit Industry Code:		
Energy, Water	-.1304724	
Mining	.9193261	
Iron, Steel	-.1157818	
Mechanical Eng.	.1814178	-.0700863
Construction	-.3476895	
Wholesale	-.1871941	
Other Trans.	-.2715754	-.4051219
Financial Inst	-.7358711	-.0465197
Insurance	-.1577707	.0472769
Service Indust.	.3314541	
Trash Removal	-.2043623	-.2055511
Educ., Sport	.6223414	1.009586
Other Services	.1213145	-.1804217
Volunt., Church	.5958084	.0954109
Public Administration	.026742	
Synthetics		-.6081662
Electrical Eng.		-.154287
Wood, Paper, Print		-.3739856
Clothing, Text.		.1946213
Health Service		.1232945
Maternity Protection or Parental Leave:		
Yes, Parental Leave	-.0208059	
Maternity Protection or Parental Leave:		
Yes, Maternity Protection		-.2637232
Sick Leave for More than 6 Weeks Previous Year	.0071316	
New Work Since Last Year:		
Yes, new work		.5737633
Binary for Having Been Dismissed by Former Employer		.0001408
Occupational Change:		
Employed No Info If Change	.1298891	
First Time Employed	-.2136909	
Employed No Change		-.2604137
Reason for Occ. Change:		
Not Applicable	-.1838295	-.0971645

To be continued

Table A.6 (continued)

Variable	Men	Women
Nature of Professional Change:		
Not Applicable	-.594456	
Returned to Past Employer After Break	.4385052	
New Position Different Employer	.3237011	.2534521
Taken On By Company	.8704918	
Changed Position Within Company	-.0375119	-.3490102
Perspective at the End of Employment Relationship:		
Yes, I already have a new employment contract	-.1823196	
No, nothing yet	.0340794	.1848657
I have not looked for a new job	.0342802	-2.014332
Perspective at the End of Employment Relationship:		
Not Applicable		-.0626813
Information Channel, New Job	-.0316574	
Actively Sought This Position	-.1278217	
Intermediate School Degree	-.0025518	
Technical School Degree	-.0509056	
Dropout, No School Degree	.513489	
Master Craftsman	-.0711813	
School-Leaving Degree Outside Germany:		
Not Applicable	.0069695	
School, No Degree	-.0406363	.0529262
School, With Degree	-.2588804	
Vocational Degree Outside Germany	.0135607	-.0136732
Vocational Degree Received:		
Not Applicable	.0894261	.2028064
Apprenticeship	-.0504512	
Technical College	-.0838145	.0772993
University, Technical College	.205434	
Engineering, Technical School (East)	.1071996	
Graduation, State Doctorate	.8121853	.7705902
University (East)		-.0085348
No Vocational Degree:		
Not Applicable	.0212117	
Type of Tertiary Degree	-.0204456	
Type of Training Participated:		
Not Applicable	-.0771829	

To be continued

Table A.6 (continued)

Variable	Men	Women
Apprenticeship	.0250551	.4565367
Now Specialized Vocational School	-.1868002	
School Of Health Care	.3099089	.1238886
Civil Service Training	-.7525602	
Company Retraining	.4668812	
Technical School		-.296344
Completed Education, Training After 2006		-.3313182
Other Income Components This Year:		
Unemployment Benefit	.0000509	.0000122
Maternity benefit		-2.07e-06
Alimony	-.000286	.0000482
Student Grants	-.0003804	.0001447
Subsistence Allowance	.0000641	
Housing Benefit		-3.66e-06
Statutory Accident Insurance		
Losses from Capital Investment	.0000195	4.21e-06
Commuting, Travel Grant	-.000141	
Unemployment Benefit II		.000047
Divorce Alimony, During Separation		.000019
Severance Payment Amount		
Severance Package, Compensation		
Change of Job in Prev. Year:		
Yes	.7768482	
Indemnity	.0000193	
Change of job in Prev. Year:		
No new work		-.3181559

Note: Coefficients of LASSO regressions by gender, dependent variable is a binary variable for FTC/PC.
Data Source: soep.v35, 2019.

Appendix B

Appendix to Chapter 3

B Appendix to Chapter 3

B.1 Descriptives by Control and Treatment Group

Table B.1: Descriptives by Control and Treatment Group

	Women (treated)						Men (control)					
	Prior Reform			After Reform			Prior Reform			After Reform		
	Mean	SD	N	Mean	SD	N	Mean	SD	N	Mean	SD	N
Age	28.98	4.22	14368	29.63	4.11	14327	29.6	4.05	16808	29.55	4.15	14141
Number of Household Members	2.68	1.22	14368	2.88	1.25	14327	2.92	1.33	16808	3.01	1.4	14141
Full-Time Working Experience	5.7	4.08	14142	4.29	3.71	14071	7.61	4.46	16564	6.47	4.44	13778
Part-Time Working Experience	1.31	2.22	14142	2.08	2.63	14071	.31	1.08	16564	.71	1.69	13778
Number of Years in FTCs	.24	.66	14368	.48	.97	13645	.2	.57	16808	.41	.87	13714
Educational Attainment:												
Less Than High School	.13	.34	14150	.11	.31	14079	.14	.35	16567	.15	.36	13744
High School	.67	.47	14150	.65	.48	14079	.69	.46	16567	.64	.48	13744
More Than High School	.2	.4	14150	.24	.43	14079	.16	.37	16567	.2	.4	13744
Marital Status:												
Married	.42	.49	14342	.42	.49	14076	.45	.5	16783	.42	.49	13787
Single	.51	.5	14342	.52	.5	14076	.51	.5	16783	.56	.5	13787
Widowed	0	.04	14342	0	.03	14076	0	.03	16783	0	.02	13787
Divorced	.05	.22	14342	.04	.19	14076	.03	.16	16783	.01	.1	13787
Separated	.02	.14	14342	.02	.14	14076	.01	.12	16783	.01	.1	13787
Employment Level of Partner:												
Partner Not Employed	.04	.2	12019	.02	.14	9039	.05	.22	11942	.04	.2	8735
Partner FTC	.05	.22	12019	.06	.23	9039	.06	.25	11942	.09	.28	8735
Partner PC	.52	.5	12019	.38	.49	9039	.38	.49	11942	.29	.45	8735
No Partner	.39	.49	12019	.54	.5	9039	.5	.5	11942	.58	.49	8735
East or West Germany:												
East Germany	.25	.43	14368	.23	.42	14327	.23	.42	16808	.23	.42	14141
West Germany	.75	.43	14368	.77	.42	14327	.77	.42	16808	.77	.42	14141
Dismissal by former Employer:												
Not Dismissed	.98	.13	13160	.98	.14	11708	.97	.16	15463	.97	.18	11336
Dismissed	.02	.13	13160	.02	.14	11708	.03	.16	15463	.03	.18	11336
Occupation:												
Managers	.03	.16	13707	.03	.18	13571	.03	.18	16183	.04	.19	13418
Professionals	.1	.3	13707	.16	.36	13571	.12	.33	16183	.16	.37	13418
Technicians and Associate Professionals	.32	.47	13707	.32	.47	13571	.15	.35	16183	.17	.37	13418
Clerical Support Workers	.21	.41	13707	.14	.35	13571	.07	.26	16183	.08	.26	13418
Services and Sales Workers	.21	.41	13707	.23	.42	13571	.05	.22	16183	.08	.27	13418
Skilled Agricultural, Forestry, and Fishery Workers	.01	.1	13707	.01	.09	13571	.01	.1	16183	.01	.11	13418
Craft and Related Trades Workers	.04	.19	13707	.03	.17	13571	.35	.48	16183	.27	.44	13418
Plant and Machine Operators and Assemblers	.03	.17	13707	.02	.13	13571	.15	.35	16183	.12	.33	13418
Elementary Occupations	.06	.24	13707	.07	.25	13571	.06	.24	16183	.08	.27	13418
Number of Co-Workers:												
Less Than 5	.11	.31	13660	.09	.28	13831	.05	.23	16169	.06	.24	13766
5 To 20	.21	.4	13660	.22	.42	13831	.19	.39	16169	.18	.39	13766
20 To 200	.28	.45	13660	.28	.45	13831	.3	.46	16169	.3	.46	13766
More Than 200	.41	.49	13660	.41	.49	13831	.45	.5	16169	.45	.5	13766
Public Service:												
Working in Public Service	.29	.46	13774	.23	.42	13941	.15	.36	16236	.13	.33	13838
Not Working in Public Service	.71	.46	13774	.77	.42	13941	.85	.36	16236	.87	.33	13838
Number of Children:												
No Children	.59	.49	14368	.48	.5	14327	.56	.5	16808	.52	.5	14141
1-3 Children	.41	.49	14368	.51	.5	14327	.43	.5	16808	.46	.5	14141
4 or More Children	.01	.08	14368	.01	.1	14327	.01	.1	16808	.02	.13	14141

Notes: Descriptives refer to covariates used in the regressions. Descriptives are displayed for Women and Men in the childbearing age, separated by prior and after the reform. Data Source: soep.v33.1, 2016.

Descriptives on personal characteristics:

The mean age of around 29 years does not differ considerably between treatment and control group. Individuals in the post-reform sample seem to be slightly better educated: The fraction of individuals with a school degree lower than high school decreases slightly for women and increases slightly for men, whereas the fraction of high school graduates decreases for both genders. Fractions for the highest category of the educational attainment increase after the reform for both genders. The fraction of married individuals is stable for women but decreases slightly for men, which indicates a different sample formation in the years after the reform.

This can also be detected by considering the employment level of the partner as the fraction with no partner is higher. The fraction of women whose partner is not employed is with 6% (2%) lower than the fraction of men. The fraction of individuals whose partner is employed on a fixed-term basis does not differ much across genders and periods for women but there seem to be more men after the reform whose partner is employed on a fixed-term basis. There are more women who have a permanently employed partner than men. The fraction of having a permanently employed partner decreases after the reform by 14 percentage points for women and by 9 percentage points for men. Regarding the state of residence, the group of East Germany refers to federal states of the former GDR and Berlin. About 23% of individuals of both sub-samples live in East Germany. Considering the number of children, I observe changes from prior to after the reform for women. Here, the fraction of women having no children decreases after the reform by 11 percentage points. The fraction of women with one to three children increases by 10 percentage points. A potential reason is that more women work after the reform and stay therefore in the sample as I only consider employed individuals.

Descriptives on work history of individuals:

The full-time working experience for women is lower than for men and decreases for both groups after the reform by about one and a half years. A potential reason could be a longer stay in education of individuals that enter the sample after the reform. The part-time working experience for women is higher than for men and increases for both genders after the reform. Treatment and control group do not differ much in the average years employed on a fixed-term basis but this time increases for both groups after the reform, which indicates an increasing trend in fixed-term employment over the considered period. The major fraction (97% to 98%) of men and women was not dismissed by their former employer.

Descriptives on firm and job characteristics:

In the occupation of managers there is no gender related difference in fractions observable: about 3% of women and 3-4% of men are employed in this occupation. The fraction of professionals increases slightly after the reform by 6 percentage points for women and 4 percentage points for men. Nevertheless, fractions of professionals are comparable for men and women. The fraction of women who work as technicians and associate professionals is nearly double the fraction of men. The fraction of clerical support workers is much higher for women (21%, 14%) than for men (7%, 8%). The same is observable for service and sales workers but with an increase in the fraction for women and men after the reform. The fraction of men in the occupation of craft and related trade workers is with 35% (27%) much higher for men than for women with 4% (3%). The same holds for plant and machine operators but to a lower extent. In elementary occupations, fractions of men and women are comparable. Considering the firm size there is no remarkable change from prior to after the reform observable.[1] The fraction of women in small firms with up to twenty employees is slightly higher than the fraction of men. The reverse in the case for the fractions in bigger firms with more than 20 employees.

[1]I recode firm size to a categorical variable indicating firm sizes of less than five, five to twenty, more than 20 but less than 200, and more than 200 employees.

B.2 Subgroup Results - OLS

Table B.2: OLS - Young Individuals With and Without Children

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Dependent Variable: Binary for working in FTC/PC									
Female	0.027***	0.023***	0.029***	0.028***	0.010*	0.007*	0.016***	0.010**	0.009*
	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)
Age		-0.079***	-0.087***	-0.087***	-0.012	-0.017**	-0.020**	-0.019**	-0.018**
		(0.006)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Age^2		0.001***	0.001***	0.001***	0.000**	0.000***	0.000***	0.000***	0.000**
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Education w.r.t. High School:									
High School			-0.051***	-0.055***	-0.034***	-0.027***	-0.001	-0.001	-0.001
			(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
More than High School			0.009	0.006	-0.024***	-0.016**	-0.018**	-0.022**	-0.021**
			(0.009)	(0.009)	(0.009)	(0.008)	(0.009)	(0.009)	(0.009)
Marital Status:									
Single			0.011*	0.006	0.003	0.004	0.004	0.006	0.012**
			(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)
Widowed			0.026	0.012	0.022	0.036	0.052	0.041	0.035
			(0.052)	(0.054)	(0.057)	(0.054)	(0.054)	(0.057)	(0.057)
Divorced			0.028**	0.025**	0.020*	0.028***	0.021**	0.024**	0.024**
			(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Separated			0.037**	0.034**	0.024	0.024*	0.018	0.020	0.022
			(0.016)	(0.016)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Number of Persons in HH			0.004**	0.004**	-0.002	-0.001	-0.000	-0.000	-0.002
			(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Emp. Level of Partner:									
Partner employed FTC			0.028***	0.028***	0.016*	0.012	0.013	0.012	0.016*
			(0.009)	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)
Partner employed PC			-0.022***	-0.021***	-0.025***	-0.022***	-0.014***	-0.016***	-0.011**
			(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
No Partner			0.004	0.006	-0.009	-0.012*	-0.006	-0.008	-0.003
			(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
West Germany				-0.037***	-0.030***	-0.028***	-0.032***	-0.027***	-0.025***
				(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Full-Time Employment Experience					-0.057***	-0.059***	-0.052***	-0.052***	-0.052***
					(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Full-Time Employment Experience^2					0.002***	0.003***	0.002***	0.002***	0.002***
					(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Part-Time Employment Experience					-0.009***	-0.012***	-0.012***	-0.013***	-0.014***
					(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Part-Time Employment Experience^2					-0.001*	-0.000	-0.000	-0.000	-0.000
					(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Indicator for Dismissal by former Employer					0.215***	0.211***	0.213***	0.216***	0.216***
					(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Number of previous FTCs						0.070***	0.066***	0.063***	0.063***
						(0.004)	(0.004)	(0.003)	(0.003)
Firm Size:									
5 to 20 Employees							0.037***	0.032***	0.032***
							(0.007)	(0.007)	(0.007)
More than 20, Less than 200 Employees							0.065***	0.054***	0.054***
							(0.007)	(0.007)	(0.007)
More than 200 Employees							0.077***	0.059***	0.059***
							(0.006)	(0.007)	(0.006)
Not working in Public Service								-0.091***	-0.091***
								(0.007)	(0.007)
Number of Children:									
1-3 Children									0.020***
									(0.006)
4 or more Children									-0.019
									(0.020)
Constant	0.076***	1.380***	1.495***	1.535***	0.475***	0.557***	0.615***	0.696***	0.671***
	(0.006)	(0.093)	(0.108)	(0.107)	(0.119)	(0.116)	(0.120)	(0.120)	(0.120)
Survey Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupational Position	No	No	No	No	No	No	Yes	Yes	Yes
Occupation	No	No	No	No	No	No	Yes	Yes	Yes
Required Training	No	No	No	No	No	No	Yes	Yes	Yes
Adj. R-Square	0.019	0.045	0.056	0.058	0.107	0.133	0.152	0.162	0.162
Number of Obs.	58,501	58,501	45,152	45,152	39,402	39,402	37,231	37,106	37,106
F-Test (p-value)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Note: Regressions are estimated with OLS. The different columns represent the specifications where controls are included sucessively. The base category for the educational attainment is *Less than High School*, for the marital status *Married*, for the employment level of the partner *Partner not employed*, for the firm size *Less than 5*, and for the number of children *No children*. Standard errors appear in parentheses and are clustered at the individual level. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. *F-Test* (p-value) denotes the p-value associated with an F-test of joint significance of the included controls. Data Source: soep.v33.1, 2016.

Table B.3: OLS - Subgroup Young Individuals Without Children

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Dependent Variable: Binary for working in FTC/PC								
Female	0.023***	0.013**	0.012*	0.013**	0.014**	0.008	0.019***	0.014**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)
Age		-0.091***	-0.098***	-0.099***	0.003	0.000	-0.002	-0.001
		(0.009)	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)
Age^2		0.001***	0.001***	0.001***	0.000	0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Education w.r.t. High School:								
High School			-0.042***	-0.045***	-0.031***	-0.023***	0.001	0.001
			(0.010)	(0.010)	(0.010)	(0.009)	(0.009)	(0.009)
More than High School			0.038***	0.036***	-0.027**	-0.012	-0.014	-0.020
			(0.013)	(0.013)	(0.012)	(0.011)	(0.012)	(0.012)
Marital Status:								
Single			0.005	0.001	0.003	0.004	0.005	0.005
			(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)
Widowed			-0.102***	-0.104***	-0.080	-0.055	-0.067	-0.075
			(0.025)	(0.027)	(0.079)	(0.078)	(0.076)	(0.100)
Divorced			0.011	0.009	0.028*	0.031**	0.022	0.024*
			(0.016)	(0.016)	(0.015)	(0.014)	(0.014)	(0.014)
Separated			0.044*	0.041*	0.043**	0.040**	0.036*	0.039**
			(0.023)	(0.023)	(0.020)	(0.019)	(0.020)	(0.019)
Number of Persons in HH			0.000	0.000	-0.000	0.000	0.001	0.001
			(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Emp. Level of Partner:								
Partner employed FTC			0.028	0.030*	0.036**	0.031*	0.038**	0.035**
			(0.018)	(0.018)	(0.017)	(0.017)	(0.017)	(0.017)
Partner employed PC			-0.032**	-0.030**	-0.009	-0.007	0.004	0.001
			(0.014)	(0.014)	(0.013)	(0.013)	(0.013)	(0.013)
No Partner			-0.004	-0.002	0.004	-0.001	0.010	0.006
			(0.015)	(0.015)	(0.014)	(0.013)	(0.013)	(0.013)
West Germany				-0.028***	-0.022***	-0.018***	-0.022***	-0.018***
				(0.008)	(0.007)	(0.006)	(0.006)	(0.006)
Full-Time Employment Experience					-0.070***	-0.074***	-0.066***	-0.065***
					(0.003)	(0.003)	(0.003)	(0.003)
Full-Time Employment Experience^2					0.003***	0.004***	0.003***	0.003***
					(0.000)	(0.000)	(0.000)	(0.000)
Part-Time Employment Experience					-0.001	-0.005	-0.008*	-0.009**
					(0.005)	(0.005)	(0.005)	(0.005)
Part-Time Employment Experience^2					-0.001	-0.000	-0.000	-0.000
					(0.001)	(0.001)	(0.001)	(0.001)
Indicator for Dismissal by former Employer					0.205***	0.200***	0.205***	0.209***
					(0.021)	(0.021)	(0.021)	(0.021)
Number of previous FTCs						0.078***	0.075***	0.071***
						(0.005)	(0.005)	(0.005)
Firm Size:								
5 to 20 Employees							0.033***	0.029***
							(0.009)	(0.009)
More than 20, Less than 200 Employees							0.072***	0.061***
							(0.009)	(0.009)
More than 200 Employees							0.077***	0.058***
							(0.009)	(0.009)
Not working in Public Service								-0.097***
								(0.008)
Constant	0.071***	1.510***	1.665***	1.690***	0.223	0.287*	0.348**	0.439***
	(0.008)	(0.125)	(0.137)	(0.137)	(0.158)	(0.155)	(0.162)	(0.162)
Survey Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupational Position	No	No	No	No	No	No	Yes	Yes
Occupation	No	No	No	No	No	No	Yes	Yes
Required Training	No	No	No	No	No	No	Yes	Yes
Adj. R-Square	0.022	0.048	0.060	0.061	0.122	0.154	0.172	0.183
Number of Obs.	31,609	31,609	25,720	25,720	22,248	22,248	21,044	20,961
F-Test (p-value)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Note: Regressions are estimated with OLS. The different columns represent the specifications where controls are included successively. The base category for the educational attainment is *Less than High School*, for the marital status *Married*, for the employment level of the partner *Partner not employed*, for the firm size *Less than 5*, and for the number of children *No children*. Standard errors appear in parentheses and are clustered at the individual level. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. *F-Test* (p-value) denotes the p-value associated with an F-test of joint significance of the included controls. Data Source: soep.v33.1, 2016.

Table B.4: OLS - Subgroup Young Individuals With Children

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Dependent Variable: Binary for working in FTC/PC									
Female	0.033***	0.036***	0.041***	0.039***	0.014	0.015*	0.019**	0.011	0.011
	(0.006)	(0.006)	(0.008)	(0.007)	(0.009)	(0.008)	(0.009)	(0.009)	(0.009)
Age		-0.071***	-0.065***	-0.067***	-0.027**	-0.032**	-0.031**	-0.030**	-0.029**
		(0.010)	(0.012)	(0.012)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Age^2		0.001***	0.001***	0.001***	0.001**	0.001***	0.001**	0.001**	0.001**
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Education w.r.t. High School:									
High School			-0.055***	-0.060***	-0.044***	-0.039***	-0.011	-0.010	-0.011
			(0.009)	(0.009)	(0.009)	(0.008)	(0.009)	(0.009)	(0.009)
More than High School			-0.022*	-0.027**	-0.047***	-0.045***	-0.033**	-0.036***	-0.037***
			(0.013)	(0.013)	(0.012)	(0.012)	(0.014)	(0.014)	(0.014)
Marital Status:									
Single			0.040***	0.027**	0.012	0.013	0.015	0.017*	0.017*
			(0.011)	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Widowed			0.021	0.003	0.011	0.019	0.033	0.022	0.022
			(0.059)	(0.062)	(0.063)	(0.060)	(0.061)	(0.064)	(0.064)
Divorced			0.023	0.020	0.012	0.019	0.012	0.015	0.016
			(0.017)	(0.017)	(0.017)	(0.016)	(0.016)	(0.016)	(0.016)
Separated			0.016	0.011	0.005	0.005	-0.004	-0.004	-0.003
			(0.022)	(0.022)	(0.021)	(0.020)	(0.020)	(0.019)	(0.019)
Number of Persons in HH			-0.004	-0.003	-0.008***	-0.007***	-0.007***	-0.007***	-0.006**
			(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Emp. Level of Partner:									
Partner employed FTC			0.021*	0.020*	0.017*	0.012	0.010	0.011	0.011
			(0.011)	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Partner employed PC			-0.018**	-0.019***	-0.016**	-0.015**	-0.009	-0.011*	-0.011*
			(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)
No Partner			0.016	0.023	0.011	0.011	0.015	0.013	0.013
			(0.015)	(0.015)	(0.014)	(0.013)	(0.014)	(0.014)	(0.014)
West Germany				-0.037***	-0.033***	-0.031***	-0.035***	-0.030***	-0.030***
				(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Full-Time Employment Experience					-0.043***	-0.044***	-0.039***	-0.038***	-0.038***
					(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Full-Time Employment Experience^2					0.002***	0.002***	0.002***	0.002***	0.002***
					(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Part-Time Employment Experience					-0.021***	-0.023***	-0.021***	-0.021***	-0.021***
					(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Part-Time Employment Experience^2					0.000	0.000	0.000	0.000	0.000
					(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Indicator for Dismissal by former Employer					0.221***	0.218***	0.213***	0.216***	0.216***
					(0.025)	(0.024)	(0.024)	(0.024)	(0.024)
Number of previous FTCs						0.060***	0.057***	0.053***	0.054***
						(0.005)	(0.005)	(0.005)	(0.005)
Firm Size:									
5 to 20 Employees							0.043***	0.037***	0.037***
							(0.010)	(0.010)	(0.010)
More than 20, Less than 200 Employees							0.057***	0.046***	0.046***
							(0.009)	(0.009)	(0.009)
More than 200 Employees							0.077***	0.061***	0.061***
							(0.009)	(0.009)	(0.009)
Not working in Public Service								-0.082***	-0.081***
								(0.010)	(0.010)
4 or more CHildren									-0.019
									(0.020)
Constant	0.082***	1.321***	1.210***	1.270***	0.714***	0.782***	0.782***	0.858***	0.842***
	(0.008)	(0.144)	(0.187)	(0.187)	(0.196)	(0.193)	(0.199)	(0.196)	(0.198)
Survey Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupational Position	No	No	No	No	No	No	Yes	Yes	Yes
Occupation	No	No	No	No	No	No	Yes	Yes	Yes
Required Training	No	No	No	No	No	No	Yes	Yes	Yes
Adj. R-Square	0.016	0.042	0.056	0.058	0.097	0.117	0.136	0.143	0.143
Number of Obs.	26,892	26,892	19,432	19,432	17,154	17,154	16,187	16,145	16,145
F-Test (p-value)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Note: Regressions are estimated with OLS. The different columns represent the specifications where controls are included sucessively. The base category for the educational attainment is *Less than High School*, for the marital status *Married*, for the employment level of the partner *Partner not employed*, for the firm size *Less than 5*, and for the number of children *No children*. Standard errors appear in parentheses and are clustered at the individual level. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. *F-Test* (p-value) denotes the p-value associated with an F-test of joint significance of the included controls. Data Source: soep.v33.1, 2016.

B.3 Subgroup Results - DiD

Table B.5: DD - Subgroup Young Individuals With or Without Children

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Dependent Variable: Binary for working in FTC/PC									
Female	0.024***	0.016***	0.019***	0.019***	0.004	0.003	0.011**	0.004	0.003
	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)
Reform 2007	0.079***	0.078***	0.068***	0.068***	0.028***	0.011**	0.010*	0.015***	0.015***
	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Reform 2007 × Female	0.007	0.017**	0.025***	0.026***	0.016*	0.012	0.013	0.016*	0.015*
	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)
Age		-0.082***	-0.090***	-0.091***	-0.013	-0.017**	-0.020**	-0.020**	-0.018**
		(0.006)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Age^2		0.001***	0.001***	0.001***	0.000**	0.000***	0.000***	0.000***	0.000**
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Education w.r.t. High School:									
High School			-0.050***	-0.054***	-0.034***	-0.028***	-0.001	-0.001	-0.001
			(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
More than High School			0.011	0.008	-0.023***	-0.017**	-0.017*	-0.022**	-0.021**
			(0.009)	(0.009)	(0.009)	(0.008)	(0.009)	(0.009)	(0.009)
Marital Status:									
Single			0.014**	0.009	0.005	0.004	0.005	0.007	0.013**
			(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)
Widowed			0.023	0.010	0.022	0.037	0.051	0.040	0.035
			(0.052)	(0.053)	(0.057)	(0.054)	(0.054)	(0.057)	(0.057)
Divorced			0.027**	0.024**	0.020*	0.028***	0.021**	0.024**	0.024**
			(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Separated			0.035**	0.032**	0.023	0.025*	0.018	0.020	0.022
			(0.016)	(0.016)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Number of Persons in HH			0.004**	0.003**	-0.002	-0.001	-0.000	-0.000	-0.002
			(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Emp. Level of Partner:									
Partner employed FTC			0.033***	0.033***	0.018**	0.012	0.013	0.013	0.017**
			(0.009)	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)
Partner employed PC			-0.021***	-0.021***	-0.025***	-0.022***	-0.014***	-0.016***	-0.011**
			(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
No Partner			0.006	0.008	-0.010	-0.013*	-0.007	-0.009	-0.004
			(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
West Germany				-0.036***	-0.030***	-0.028***	-0.032***	-0.027***	-0.025***
				(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Full-Time Employment Experience					-0.057***	-0.059***	-0.052***	-0.051***	-0.051***
					(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Full-Time Employment Experience^2					0.002***	0.003***	0.002***	0.002***	0.002***
					(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Part-Time Employment Experience					-0.009***	-0.012***	-0.012***	-0.013***	-0.014***
					(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Part-Time Employment Experience^2					-0.001**	-0.000	-0.000	-0.000	-0.000
					(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Indicator for Dismissal by former Employer					0.216***	0.211***	0.213***	0.216***	0.216***
					(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Number of previous FTCs						0.069***	0.066***	0.063***	0.063***
						(0.004)	(0.003)	(0.003)	(0.003)
Firm Size:									
5 to 20 Employees							0.037***	0.032***	0.032***
							(0.007)	(0.007)	(0.007)
More than 20, Less than 200 Employees							0.064***	0.054***	0.053***
							(0.007)	(0.007)	(0.007)
More than 200 Employees							0.076***	0.058***	0.058***
							(0.006)	(0.006)	(0.006)
Public Service: No								-0.091***	-0.091***
								(0.007)	(0.007)
Number of Children:									
1-3 Children									0.020***
									(0.006)
4 or more Children									-0.019
									(0.020)
Constant	0.102***	1.455***	1.564***	1.605***	0.493***	0.556***	0.621***	0.708***	0.682***
	(0.003)	(0.093)	(0.108)	(0.108)	(0.119)	(0.116)	(0.121)	(0.120)	(0.120)
Occupational Position	No	No	No	No	No	No	Yes	Yes	Yes
Occupation	No	No	No	No	No	No	Yes	Yes	Yes
Required Training	No	No	No	No	No	No	Yes	Yes	Yes
Adj. R-Square	0.015	0.041	0.053	0.055	0.107	0.133	0.152	0.161	0.162
Number of Obs.	58,501	58,501	45,152	45,152	39,402	39,402	37,231	37,106	37,106
F-Test (p-value)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Note: Regressions are estimated with OLS. The different columns represent the specifications where controls are included sucessively. The base category for the educational attainment is *Less than High School*, for the marital status *Married*, for the employment level of the partner *Partner not employed*, for the firm size *Less than 5*, and for the number of Children *No Children*. Standard errors appear in parentheses and are clustered at the individual level. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. *F*-Test (p-value) denotes the p-value associated with an *F*-Test of joint significance of the included controls. Data Source: soep.v33.1, 2016.

Table B.6: DD - Subgroup Young Individuals With Children

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Dependent Variable: Binary for working in FTC/PC									
Female	0.039***	0.039***	0.039***	0.036***	0.015	0.019**	0.020**	0.010	0.010
	(0.007)	(0.007)	(0.008)	(0.008)	(0.010)	(0.009)	(0.010)	(0.010)	(0.010)
Reform 2007	0.080***	0.080***	0.070***	0.071***	0.037***	0.026***	0.025***	0.029***	0.029***
	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)
Reform 2007 $\times$ Female	-0.011	-0.005	0.007	0.007	-0.004	-0.010	-0.000	0.005	0.005
	(0.011)	(0.011)	(0.013)	(0.013)	(0.013)	(0.012)	(0.013)	(0.013)	(0.013)
Age		-0.074***	-0.065***	-0.067***	-0.026**	-0.029**	-0.030**	-0.030**	-0.029**
		(0.010)	(0.012)	(0.012)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Age^2		0.001***	0.001***	0.001***	0.001**	0.001***	0.001**	0.001**	0.001**
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Education w.r.t. High School:									
High School			-0.055***	-0.060***	-0.044***	-0.039***	-0.011	-0.011	-0.011
			(0.009)	(0.009)	(0.009)	(0.008)	(0.009)	(0.009)	(0.009)
More than High School			-0.022*	-0.027**	-0.047***	-0.046***	-0.033**	-0.036***	-0.036***
			(0.013)	(0.013)	(0.012)	(0.012)	(0.014)	(0.014)	(0.014)
Marital Status:									
Single			0.041***	0.029***	0.011	0.011	0.014	0.016*	0.016*
			(0.011)	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Widowed			0.017	0.000	0.011	0.019	0.032	0.022	0.022
			(0.059)	(0.061)	(0.063)	(0.061)	(0.061)	(0.064)	(0.064)
Divorced			0.023	0.020	0.012	0.019	0.012	0.015	0.016
			(0.017)	(0.016)	(0.017)	(0.016)	(0.016)	(0.016)	(0.016)
Separated			0.014	0.009	0.006	0.008	-0.002	-0.002	-0.002
			(0.022)	(0.022)	(0.021)	(0.020)	(0.020)	(0.020)	(0.020)
Number of Persons in HH			-0.004	-0.003	-0.008***	-0.007***	-0.007***	-0.008***	-0.006**
			(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Emp. Level of Partner:									
Partner employed FTC			0.024**	0.023**	0.016	0.010	0.009	0.010	0.010
			(0.011)	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Partner employed PC			-0.018**	-0.020***	-0.017**	-0.016***	-0.010	-0.011*	-0.012*
			(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)
No Partner			0.019	0.026*	0.011	0.011	0.014	0.012	0.012
			(0.015)	(0.015)	(0.014)	(0.013)	(0.014)	(0.014)	(0.014)
West Germany				-0.036***	-0.033***	-0.032***	-0.036***	-0.030***	-0.031***
				(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Full-Time Employment Experience					-0.043***	-0.044***	-0.039***	-0.038***	-0.038***
					(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Full-Time Employment Experience^2					0.002***	0.002***	0.002***	0.001***	0.001***
					(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Part-Time Employment Experience					-0.021***	-0.023***	-0.022***	-0.021***	-0.021***
					(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Part-Time Employment Experience^2					0.000	0.000	0.000	0.000	0.000
					(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Indicator for Dismissal by former Employer					0.222***	0.218***	0.213***	0.216***	0.216***
					(0.025)	(0.024)	(0.024)	(0.024)	(0.024)
Number of previous FTCs						0.058***	0.055***	0.052***	0.052***
						(0.005)	(0.005)	(0.005)	(0.005)
Firm Size:									
5 to 20 Employees							0.042***	0.036***	0.036***
							(0.010)	(0.010)	(0.010)
More than 20, Less than 200 Employees							0.056***	0.046***	0.045***
							(0.009)	(0.009)	(0.009)
More than 200 Employees							0.076***	0.060***	0.060***
							(0.009)	(0.009)	(0.009)
Public Service: No								-0.083***	-0.082***
								(0.010)	(0.010)
4 or more Children									-0.020
									(0.020)
Constant	0.086***	1.372***	1.221***	1.283***	0.700***	0.738***	0.770***	0.857***	0.841***
	(0.004)	(0.144)	(0.187)	(0.187)	(0.197)	(0.193)	(0.200)	(0.197)	(0.199)
Occupational Position	No	No	No	No	No	No	Yes	Yes	Yes
Occupation	No	No	No	No	No	No	Yes	Yes	Yes
Required Training	No	No	No	No	No	No	Yes	Yes	Yes
Adj. R-Square	0.015	0.041	0.055	0.057	0.097	0.116	0.135	0.143	0.143
Number of Obs.	26,892	26,892	19,432	19,432	17,154	17,154	16,187	16,145	16,145
F-Test (p-value)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Note: Regressions are estimated with OLS. The different columns represent the specifications where controls are included sucessively. The base category for the educational attainment is *Less than High School*, for the marital status *Married*, for the employment level of the partner *Partner not employed*, for the firm size *Less than 5*, and for the number of Children *No Children*. Standard errors appear in parentheses and are clustered at the individual level. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. F-Test (p-value) denotes the p-value associated with an F-Test of joint significance of the included controls. Data Source: soep.v33.1, 2016.

Table B.7: DD - Subgroup Young Individuals Without Children

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Dependent Variable: Binary for working in FTC/PC								
Female	0.012*	-0.000	-0.001	0.000	0.004	-0.003	0.010	0.005
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)	(0.007)	(0.007)
Reform 2007	0.080***	0.077***	0.065***	0.065***	0.019***	-0.004	-0.005	0.001
	(0.007)	(0.007)	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)
Reform 2007 × Female	0.025**	0.032***	0.034***	0.034***	0.028**	0.028**	0.022**	0.023**
	(0.011)	(0.011)	(0.012)	(0.012)	(0.012)	(0.011)	(0.011)	(0.011)
Age		-0.094***	-0.103***	-0.103***	0.002	0.000	-0.002	-0.002
		(0.009)	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)
Age^2		0.001***	0.002***	0.002***	0.000	0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Education w.r.t. High School:								
High School			-0.040***	-0.042***	-0.030***	-0.023***	0.002	0.002
			(0.010)	(0.010)	(0.010)	(0.009)	(0.009)	(0.009)
More than High School			0.042***	0.040***	-0.026**	-0.012	-0.013	-0.018
			(0.013)	(0.013)	(0.012)	(0.011)	(0.012)	(0.012)
Marital Status:								
Single			0.009	0.006	0.006	0.005	0.006	0.007
			(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)
Widowed			-0.103***	-0.105***	-0.083	-0.057	-0.073	-0.081
			(0.022)	(0.024)	(0.081)	(0.082)	(0.081)	(0.104)
Divorced			0.010	0.007	0.027*	0.030**	0.022	0.024*
			(0.016)	(0.016)	(0.015)	(0.014)	(0.014)	(0.014)
Separated			0.042*	0.040*	0.041**	0.039**	0.035*	0.038*
			(0.023)	(0.023)	(0.020)	(0.019)	(0.020)	(0.019)
Number of Persons in HH			-0.000	-0.000	-0.001	0.000	0.000	0.001
			(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Emp. Level of Partner:								
Partner employed FTC			0.034*	0.036**	0.039**	0.032*	0.039**	0.037**
			(0.018)	(0.018)	(0.017)	(0.017)	(0.017)	(0.017)
Partner employed PC			-0.034**	-0.031**	-0.010	-0.008	0.004	0.001
			(0.014)	(0.014)	(0.013)	(0.013)	(0.013)	(0.013)
No Partner			-0.003	-0.000	0.003	-0.002	0.009	0.005
			(0.015)	(0.015)	(0.014)	(0.013)	(0.013)	(0.013)
West Germany				-0.028***	-0.022***	-0.018***	-0.022***	-0.018***
				(0.008)	(0.007)	(0.006)	(0.006)	(0.006)
Full-Time Employment Experience					-0.070***	-0.074***	-0.066***	-0.065***
					(0.003)	(0.003)	(0.003)	(0.003)
Full-Time Employment Experience^2					0.003***	0.004***	0.003***	0.003***
					(0.000)	(0.000)	(0.000)	(0.000)
Part-Time Employment Experience					-0.001	-0.006	-0.008*	-0.009**
					(0.005)	(0.005)	(0.005)	(0.005)
Part-Time Employment Experience^2					-0.001	-0.000	-0.000	-0.000
					(0.001)	(0.001)	(0.001)	(0.001)
Indicator for Dismissal by former Employer					0.206***	0.201***	0.205***	0.209***
					(0.021)	(0.021)	(0.021)	(0.021)
Number of previous FTCs						0.079***	0.075***	0.072***
						(0.005)	(0.005)	(0.005)
Firm Size:								
5 to 20 Employees							0.033***	0.028***
							(0.009)	(0.009)
More than 20, Less than 200 Employees							0.071***	0.060***
							(0.009)	(0.009)
More than 200 Employees							0.076***	0.057***
							(0.009)	(0.009)
Public Service: No								-0.096***
								(0.008)
Constant	0.115***	1.612***	1.769***	1.794***	0.250	0.299*	0.353**	0.447***
	(0.004)	(0.125)	(0.138)	(0.138)	(0.159)	(0.155)	(0.163)	(0.162)
Occupational Position	No	No	No	No	No	No	Yes	Yes
Occupation	No	No	No	No	No	No	Yes	Yes
Required Training	No	No	No	No	No	No	Yes	Yes
Adj. R-Square	0.017	0.043	0.055	0.056	0.121	0.154	0.171	0.183
Number of Obs.	31,609	31,609	25,720	25,720	22,248	22,248	21,044	20,961
F-Test (p-value)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Note: Regressions are estimated with OLS. The different columns represent the specifications where controls are included successively. The base category for the educational attainment is *Less than High School*, for the marital status *Married*, for the employment level of the partner *Partner not employed*, for the firm size *Less than 5*, and for the number of Children *No Children*. Standard errors appear in parentheses and are clustered at the individual level. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. *F*-Test (p-value) denotes the p-value associated with an *F*-Test of joint significance of the included controls. Data Source: soep.v33.1, 2016.

B.4 Results - DDD

Table B.8: Regression Results Reform DDD

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Dependent Variable: Binary for working in FTC/PC									
Female	0.021***	0.022***	0.026***	0.025***	0.001	0.005*	0.002	-0.003	-0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
Reform 2007	0.020***	0.022***	0.015***	0.016***	0.003	-0.008***	-0.006***	-0.005**	-0.006**
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Childbearing Age	0.060***	-0.049***	-0.041***	-0.041***	-0.046***	-0.047***	-0.045***	-0.046***	-0.045***
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
Female $\times$ Childbearing Age	0.003	-0.006	-0.003	-0.002	0.011*	0.006	0.009	0.010*	0.008
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
Female $\times$ Reform 2007	0.015***	0.015***	0.014***	0.015***	0.009**	0.004	0.006	0.008**	0.007*
	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Reform 2007 $\times$ Childbearing Age	0.059***	0.056***	0.055***	0.054***	0.033***	0.031***	0.026***	0.027***	0.028***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
Female $\times$ Reform 2007 $\times$ Childbearing Age	-0.008	0.002	0.009	0.009	0.014	0.016*	0.017*	0.016*	0.016*
	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)
Age		-0.032***	-0.028***	-0.028***	-0.010***	-0.012***	-0.012***	-0.012***	-0.014***
		(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age^2		0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Education w.r.t. High School:									
High School			-0.033***	-0.037***	-0.026***	-0.021***	0.008**	0.008**	0.008**
			(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
More than High School			-0.020***	-0.023***	-0.034***	-0.029***	0.004	0.003	0.003
			(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Marital Status:									
Single			0.018***	0.015***	0.011***	0.010***	0.010***	0.011***	0.014***
			(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Widowed			-0.008	-0.011	-0.006	-0.003	-0.007	-0.008	-0.009
			(0.011)	(0.011)	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)
Divorced			0.023***	0.022***	0.016***	0.019***	0.015***	0.016***	0.015***
			(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Separated			0.019***	0.017**	0.009	0.014**	0.013**	0.013**	0.013**
			(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Number of Persons in HH			0.006***	0.006***	0.002**	0.004***	0.004***	0.003***	-0.000
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Emp. Level of Partner:									
Partner employed FTC			0.030***	0.030***	0.020***	0.017***	0.018***	0.018***	0.019***
			(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Partner employed PC			-0.019***	-0.020***	-0.020***	-0.019***	-0.013***	-0.014***	-0.012***
			(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
No Partner			0.011**	0.012**	0.002	0.002	0.004	0.003	0.004
			(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
West Germany				-0.031***	-0.032***	-0.026***	-0.024***	-0.022***	-0.022***
				(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Full-Time Employment Experience					-0.016***	-0.016***	-0.013***	-0.013***	-0.013***
					(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Full-Time Employment Experience^2					0.000***	0.000***	0.000***	0.000***	0.000***
					(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Part-Time Employment Experience					-0.007***	-0.008***	-0.008***	-0.008***	-0.008***
					(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Part-Time Employment Experience^2					-0.000	0.000	0.000*	0.000*	0.000**
					(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Indicator for Dismissal by former Employer					0.225***	0.218***	0.217***	0.220***	0.220***
					(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Number of previous FTCs						0.057***	0.055***	0.054***	0.054***
						(0.002)	(0.002)	(0.002)	(0.002)
Firm Size:									
5 to 20 Employees							0.022***	0.019***	0.019***
							(0.004)	(0.004)	(0.004)
More than 20, Less than 200 Employees							0.037***	0.030***	0.030***
							(0.004)	(0.004)	(0.004)
More than 200 Employees							0.038***	0.029***	0.029***
							(0.004)	(0.004)	(0.004)
Public Service: No								-0.041***	-0.041***
								(0.003)	(0.003)
Number of Children:									
1-3 Children									0.017***
									(0.003)
4 or more Children									0.021***
									(0.008)
Constant	0.042***	0.796***	0.706***	0.733***	0.421***	0.440***	0.278***	0.329***	0.376***
	(0.002)	(0.027)	(0.033)	(0.032)	(0.035)	(0.033)	(0.036)	(0.036)	(0.037)
Occupational Position	No	No	No	No	No	No	Yes	Yes	Yes
Occupation	No	No	No	No	No	No	Yes	Yes	Yes
Required training	No	No	No	No	No	No	Yes	Yes	Yes
Adj. R-Square	0.028	0.041	0.048	0.050	0.075	0.109	0.121	0.125	0.126
Number of Obs.	184,698	184,698	138,549	138,549	126,505	126,505	121,469	121,109	121,109
F-Test (p-value)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Note: Regressions are estimated with OLS. The different columns represent the specifications where controls are included successively. The base category for the educational attainment is *Less than High School*, for the marital status *Married*, for the employment level of the partner *Partner not employed*, for the firm size *Less than 5*, and for the number of Children *No Children*. Standard errors appear in parentheses and are clustered at the individual level. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. *F*-Test (p-value) denotes the p-value associated with an *F*-Test of joint significance of the included controls. Data Source: soep.v33.1, 2016.

B.5 Differences in Fractions

Figure B.1: Difference in Fractions of FTC Workers by Gender for Individuals in Both Age Groups

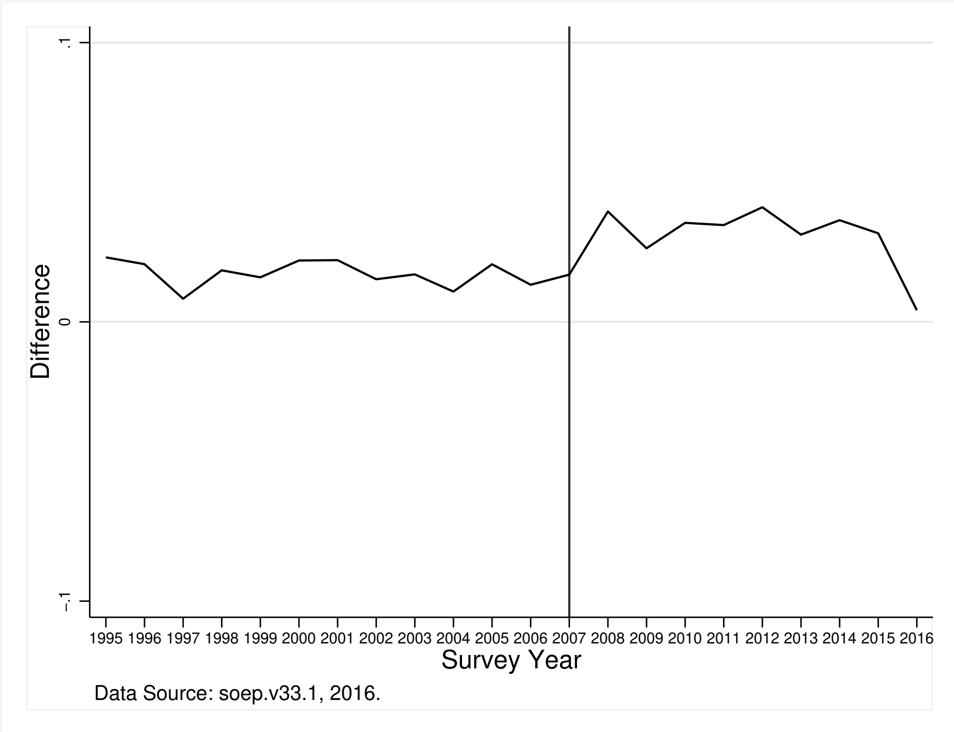


Figure B.2: Difference in Fractions of FTC Workers by Gender for Individuals of Childbearing Age

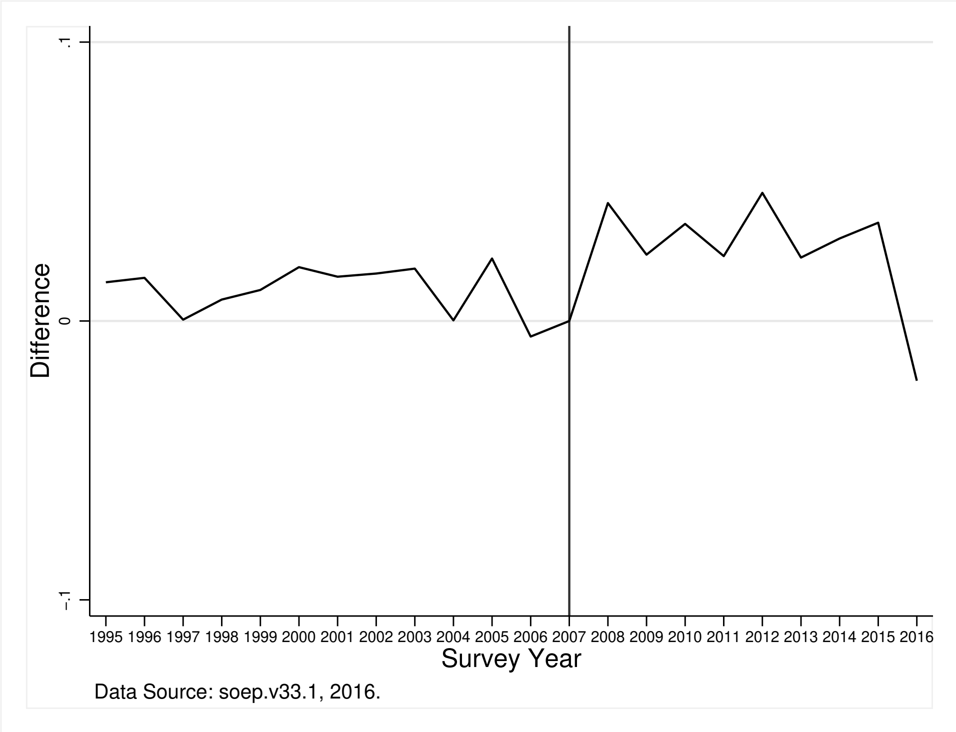
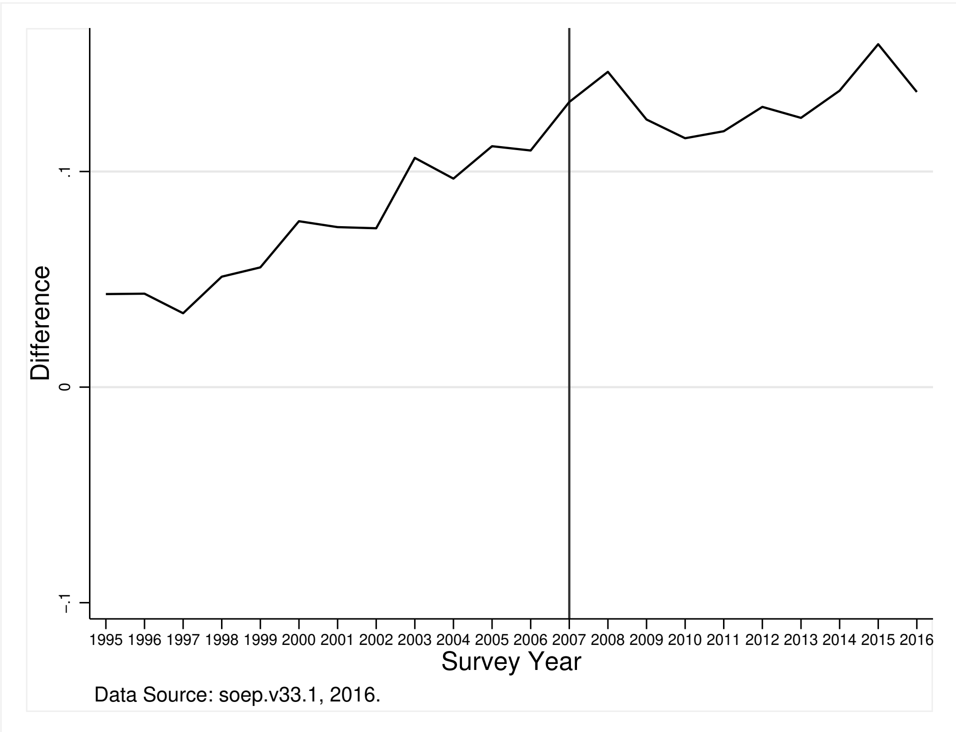


Figure B.3: Difference in Fractions of FTC Workers Comparing Women of Childbearing Age to Men and Women of Older Age



Appendix C

Appendix to Chapter 4

C Appendix to Chapter 4

C.1 Unemployment, Non-Employment, and Population Change, EU-27, Eurozone, and USA, 2006-2016

Table C.1: Unemployment, Non-Employment, and Population Change, EU-27, Eurozone, and USA, 2006-2016

	OLS EU-27/EFTA	OLS Eurozone	OLS USA	FE EU-27/EFTA	FE Eurozone	FE USA
Specifications with Lagged Relative Unemployment						
NUTS-1/States						
log rel. unemp.	-0.010***	-0.011**	-0.005	-0.030***	-0.028***	-0.021***
(s.e.)	(0.003)	(0.005)	(0.007)	(0.003)	(0.004)	(0.007)
log rel. income	0.013***	0.010	0.021***	-0.017**	0.036*	0.023
(s.e.)	(0.002)	(0.007)	(0.007)	(0.009)	(0.021)	(0.014)
R2 / R2 within	0.200	0.124	0.430	0.162	0.195	0.559
No. regions	98	61	51	98	61	51
No. time periods	11	11	11	11	11	11
No. observations	1’068	661	510	1’068	661	510
NUTS-2/SuperPUMA						
log rel. unemp.	-0.005**	-0.006**	-0.007**	-0.027***	-0.026***	-0.015***
(s.e.)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.005)
log rel. income	0.012***	0.006	0.010	-0.025***	0.014	0.005
(s.e.)	(0.001)	(0.004)	(0.007)	(0.006)	(0.010)	(0.016)
R2 / R2 within	0.144	0.102	0.170	0.125	0.195	0.214
No. regions	263	168	230	263	168	230
No. time periods	11	11	11	11	11	11
No. observations	2’856	1’813	2’300	2’856	1’813	2’300
Specifications with Lagged Relative Non-Employment						
NUTS-1/States						
log rel. non-emp.	-0.001	0.001	0.012	-0.109***	-0.095***	-0.058**
(s.e.)	(0.003)	(0.007)	(0.008)	(0.012)	(0.016)	(0.023)
log rel. income	0.008***	0.016***	0.019***	-0.013	0.043**	0.036***
(s.e.)	(0.001)	(0.002)	(0.006)	(0.009)	(0.021)	(0.013)
R2 / R2 within	0.177	0.102	0.432	0.162	0.186	0.556
No. regions	98	61	51	98	61	51
No. time periods	11	11	11	11	11	11
No. observations	1’072	665	510	1’072	665	510
NUTS-2/SuperPUMA						
log rel. non-emp.	0.000	0.008	-0.000	-0.096***	-0.088***	-0.034**
(s.e.)	(0.005)	(0.006)	(0.007)	(0.008)	(0.009)	(0.015)
log rel. income	0.014***	0.013***	0.011*	-0.020***	0.018*	0.014
(s.e.)	(0.002)	(0.004)	(0.006)	(0.006)	(0.009)	(0.016)
R2 / R2 within	0.135	0.090	0.165	0.119	0.167	0.212
No. regions	263	168	230	263	168	230
No. time periods	11	11	11	11	11	11
No. observations	2’864	1’821	2’300	2’864	1’821	2’300

Note: Pooled ordinary least squares (OLS) and region fixed effects (FE) regressions. Standard errors clustered at the regional level appear in parentheses. All regressions include year fixed effects. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Source: European Labour Force Survey, Eurostat Regional Database, American Community Survey.

C.2 Regressions at the District Level by Gender

Table C.2: Regressions at the District Level by Gender

	OLS (w)	OLS (m)	FE (w)	FE (m)
Specifications with Lagged Relative Unemployment				
Unemployment, Rounds 62-68				
log rel. unemp.	-0.001	-0.001	-0.002	0.000
(s.e.)	(0.002)	(0.002)	(0.003)	(0.003)
log rel. wage	0.006***	0.007***	0.098***	0.135***
(s.e.)	(0.002)	(0.002)	(0.012)	(0.013)
Constant	0.028***	0.016***	0.009*	-0.008*
(s.e.)	(0.005)	(0.005)	(0.004)	(0.005)
R2 / R2 within	0.016	0.012	0.094	0.129
No. regions	570	570	570	570
No. observations	1,590	1,590	1,590	1,590
Unemployment, Rounds 60-68				
log rel. unemp.	-0.002	-0.002	-0.000	-0.000
(s.e.)	(0.002)	(0.002)	(0.003)	(0.003)
log rel. wage	0.015***	0.016***	0.187***	0.208***
(s.e.)	(0.004)	(0.004)	(0.028)	(0.027)
Constant	0.034***	0.037***	-0.009	-0.012*
(s.e.)	(0.008)	(0.008)	(0.006)	(0.006)
R2 / R2 within	0.028	0.028	0.231	0.248
No. regions	570	570	570	570
No. observations	2,081	2,081	2,081	2,081
Specifications with Lagged Relative Non-Employment				
Non-Employment, Rounds 62-68				
log rel. non-emp.	-0.007	-0.011	-0.057***	-0.070***
(s.e.)	(0.008)	(0.008)	(0.016)	(0.018)
log rel. wage	0.008***	0.007***	0.105***	0.134***
(s.e.)	(0.002)	(0.002)	(0.012)	(0.013)
Constant	0.029***	0.017***	0.001	-0.019***
(s.e.)	(0.004)	(0.005)	(0.005)	(0.005)
R2 / R2 within	0.020	0.012	0.114	0.136
No. regions	1,708	1,708	1,708	1,708
No. observations	570	570	570	570
Non-Employment, Rounds 60-68				
log rel. non-emp.	-0.008	-0.008	-0.082***	-0.085***
(s.e.)	(0.010)	(0.010)	(0.017)	(0.015)
log rel. wage	0.017***	0.018***	0.197***	0.211***
(s.e.)	(0.004)	(0.004)	(0.024)	(0.024)
Constant	0.041***	0.048***	-0.020***	-0.017**
(s.e.)	(0.008)	(0.008)	(0.007)	(0.007)
R2 / R2 within	0.037	0.036	0.254	0.258
No. regions	570	570	570	570
No. observations	2,273	2,273	2,273	2,273

Note: Regressions are estimated by pooled ordinary least squares (OLS) and fixed effects (FE). (w) and (m) denote the female and male population, respectively. Standard errors clustered at the district level appear in parentheses. All regressions include year fixed effects. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Data Source: Indian EUS-NSSO.

Table C.3: Regressions at the District Level by Gender, Working Age Population Younger than 50

	OLS (w)	OLS (m)	FE (w)	FE (m)
Specifications with Lagged Relative Unemployment				
Unemployment, Rounds 62-68				
log rel. unemp.	-0.001	-0.001	-0.001	0.002
(s.e.)	(0.002)	(0.002)	(0.003)	(0.003)
log rel. wage	0.007***	0.008***	0.110***	0.155***
(s.e.)	(0.002)	(0.002)	(0.012)	(0.013)
Constant	0.024***	0.011**	0.002	-0.018***
(s.e.)	(0.005)	(0.005)	(0.005)	(0.005)
R2 / R2 within	0.013	0.014	0.102	0.150
No. regions	570	570	570	570
No. observations	1,587	1,587	1,587	1,587
Unemployment, Rounds 60-68				
log rel. unemp.	-0.001	-0.001	0.001	0.002
(s.e.)	(0.002)	(0.002)	(0.003)	(0.003)
log rel. wage	0.016***	0.017***	0.198***	0.222***
(s.e.)	(0.004)	(0.004)	(0.030)	(0.028)
Constant	0.040***	0.041***	-0.004	-0.009
(s.e.)	(0.009)	(0.009)	(0.006)	(0.006)
R2 / R2 within	0.029	0.030	0.237	0.261
No. regions	570	570	570	570
No. observations	2,078	2,078	2,078	2,078
Specifications with Lagged Relative Non-Employment				
Non-Employment, Rounds 62-68				
log rel. non-emp.	-0.012	-0.013	-0.070***	-0.069***
(s.e.)	(0.008)	(0.009)	(0.017)	(0.019)
log rel. wage	0.008***	0.008***	0.118***	0.154***
(s.e.)	(0.002)	(0.003)	(0.012)	(0.014)
Constant	0.025***	0.011**	-0.007	-0.029***
(s.e.)	(0.005)	(0.005)	(0.005)	(0.005)
R2 / R2 within	0.017	0.014	0.127	0.154
No. regions	570	570	570	570
No. observations	1,707	1,707	1,707	1,707
Non-Employment, Rounds 60-68				
log rel. non-emp.	-0.009	-0.007	-0.080***	-0.078***
(s.e.)	(0.010)	(0.010)	(0.017)	(0.015)
log rel. wage	0.018***	0.018***	0.213***	0.228***
(s.e.)	(0.004)	(0.004)	(0.027)	(0.025)
Constant	0.045***	0.051***	-0.019**	-0.018**
(s.e.)	(0.008)	(0.008)	(0.007)	(0.007)
R2 / R2 within	0.037	0.037	0.272	0.278
No. regions	570	570	570	570
No. observations	2,272	2,272	2,272	2,272

Note: Regressions are estimated by pooled ordinary least squares (OLS) and fixed effects (FE). (w) and (m) denote the female and male population, respectively. Standard errors clustered at the district level appear in parentheses. All regressions include year fixed effects. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Data Source: Indian EUS-NSSO.

C.3 Regressions at the District Level by Group

Table C.4: Regressions at the District Level for (1) “Others” and (2) “Disadvantaged Groups”

	OLS (1)	OLS (2)	FE (1)	FE (2)
Specifications with Lagged Relative Unemployment				
Unemployment, Rounds 62-68				
log rel. unemp.	0.019***	-0.017***	0.001	-0.003
(s.e.)	(0.003)	(0.003)	(0.002)	(0.003)
log rel. wage	-0.002	0.005	0.038***	0.103***
(s.e.)	(0.004)	(0.004)	(0.009)	(0.011)
Constant	0.259***	0.540***	0.240***	0.537***
(s.e.)	(0.008)	(0.007)	(0.003)	(0.004)
R2 / R2 within	0.026	0.027	0.020	0.109
No. regions	565	565	565	565
No. observations	1,548	1,548	1,548	1,548
Unemployment, Rounds 60-68				
log rel. unemp.	0.021***	-0.020***	0.002	-0.004*
(s.e.)	(0.003)	(0.002)	(0.002)	(0.002)
log rel. wage	-0.001	0.010**	0.055***	0.156***
(s.e.)	(0.004)	(0.004)	(0.009)	(0.019)
Constant	0.261***	0.537***	0.239***	0.534***
(s.e.)	(0.008)	(0.007)	(0.003)	(0.004)
R2 / R2 within	0.029	0.031	0.042	0.190
No. regions	566	566	566	566
No. observations	2,016	2,016	2,016	2,016
Specifications with Lagged Relative Non-Employment				
Non-Employment, Rounds 62-68				
log rel. non-emp.	0.145***	-0.118***	-0.035***	-0.045***
(s.e.)	(0.012)	(0.011)	(0.011)	(0.016)
log rel. wage	0.001	0.003	0.040***	0.103***
(s.e.)	(0.004)	(0.004)	(0.008)	(0.012)
Constant	0.257***	0.545***	0.232***	0.535***
(s.e.)	(0.007)	(0.007)	(0.003)	(0.004)
R2 / R2 within	0.073	0.062	0.030	0.113
No. regions	566	566	566	566
No. observations	1,660	1,660	1,660	1,660
Non-Employment, Rounds 60-68				
log rel. non-emp.	0.132***	-0.116***	-0.042***	-0.069***
(s.e.)	(0.011)	(0.012)	(0.013)	(0.016)
log rel. wage	0.006	0.008**	0.067***	0.164***
(s.e.)	(0.004)	(0.004)	(0.011)	(0.018)
Constant	0.256***	0.544***	0.228***	0.525***
(s.e.)	(0.007)	(0.007)	(0.004)	(0.005)
R2 / R2 within	0.064	0.055	0.068	0.205
No. regions	567	567	567	567
No. observations	2,194	2,194	2,194	2,194

Note: Regressions are estimated by pooled ordinary least squares (OLS) and fixed effects (FE). (1) denotes “Others” and (2) denotes the disadvantaged groups as defined by the EUS-NSSO data (“ST”, “SC”, “OBC”). Standard errors clustered at the district level appear in parentheses. All regressions include year fixed effects. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Data Source: Indian EUS-NSSO.