Job mobility, wages and job satisfaction

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Thomas Cornelißen, December 2008

Abstract

The thesis consists of an empirical part and a methodological part. An overview of the whole analysis and of the main findings is presented in the introduction (Chapter 1). The following three chapters form the empirical part of the thesis with empirical analyses of the interrelation of job mobility, wages and job satisfaction. Chapter 2 uses German household panel data to analyze the association of downward wage rigidity with several types of external and internal job mobility. Chapter 3 uses German linked employer-employee data to estimate wage and job duration functions with individual and firm fixed effects. In a second step, the correlations of the unobserved heterogeneity components (fixed effects) are analyzed. Chapter 4 then introduces job satisfaction and non-pecuniary job characteristics into the analysis. Drawing again on household panel data, that chapter analyzes the conditions under which low job satisfaction leads to job search, and under which job search leads to job changes. Job satisfaction itself is explained by a set of detailed job characteristics.

The methodological part of the thesis contains two chapters that include methodological tools that were developed in order to conduct the analyses presented in the empirical part. These tools were made available for public use as programs in the econometrics software Stata. In chapter 5 standard errors of the marginal effects in a heteroskedastic probit model are derived analytically using the delta method. In chapter 6 a sparse matrix algortihm for a memory-saving way to estimate a fixed-effects model with two high-dimensional fixed effects is developed.

Keywords: job mobility, wages, wage rigidity, job satisfaction, heteroskedastic probit model, fixed-effects model.

Kurzusammenfassung

Diese Dissertation untergliedert sich in einen empirischen und einen methodischen Teil. Die Einleitung in Kapitel 1 gibt zunächst einen Überblick über den Inhalt und die Forschungsergebnisse der gesamten Dissertation. Die folgenden drei Kapitel bilden den empirischen Teil, welcher sich mit dem Zusammenwirken von Arbeitsplatzwechseln, Löhnen und Arbeitszufriedenheit beschäftigt. Auf der Basis von deutschen Haushaltspaneldaten arbeitet Kapitel 2 den Zusammenhang zwischen Abwärtslohnstarrheit und verschiedenen Formen von internen und externen Arbeitsplatzwechseln heraus. Kapitel 3 stützt sich auf die Analyse von deutschen integrierten Betriebs- und Personendaten. Hier werden Lohn- und Beschäftigungsdauerfunktionen mit fixen Betriebs- und Personeneffekten geschätzt. Anschließend werden die Korrelationen zwischen den fixen Lohn- und Beschäftigungsdauereffekten analysiert. Kapitel 4 führt die Arbeitszufriedenheit und nichtmonetäre Arbeitsplatzeigenschaften in die Analyse ein. Hier wird auf Basis von Haushaltspaneldaten untersucht, unter welchen Bedingungen geringe Arbeitszufriedenheit zu Arbeitsplatzsuche führt, und unter welchen Bedingungen die Arbeitsplatzsuche zu Arbeitsplatzwechseln führt. Gleichzeitig wird die Arbeitszufriedenheit durch detaillierte Arbeitsplatzeigenschaften erklärt.

Der methodische Teil der Dissertation enthält zwei Kapitel, in denen methodische Lösungen entwickelt werden, welche für die Analyse im empirischen Teil benötigt wurden. Diese sind als Programme für die Ökonometriesoftware Stata umgesetzt und für andere Nutzer öffentlich zugänglich gemacht worden. In Kapitel 5 werden unter Verwendung der Deltamethode Standardfehler für die marginalen Effekte im heteroskedastischen Probitmodel analytisch hergeleitet. In Kapitel 6 wird ein Algorithmus für die arbeitsspeichersparende Berechnung eines Fixed-Effects-Modells mit zwei hochdimensionalen fixen Effekten entwickelt.

Schlagwörter: Arbeitsplatzwechsel, Löhne, Lohnrigidität, Arbeitszufriedenheit, heteroskedastisches Probitmodell, Fixed-Effects-Modell.

Contents

Chapter 1

Introduction

> If in the same neighbourhood, there was any employment evidently either more or less advantageous than the rest, so many people would crowd into it in the one case, and so many would desert it in the other, that its advantages would soon return to the level of other employments. [...] Every man's interest would prompt him to seek the advantageous, and to shun the disadvantageous employment.
> **Adam Smith, *Wealth of Nations*, Book I, Chapter X, 1776, p. 95.**

> Because it happens more or less routinely, the efficiency with which a market system allocates labor in the economy is often taken for granted. It is, however, a monumental task. How do all the different jobs and all the diverse individuals in any one of our larger cities get matched up? How is it that there are enough truck drivers to deliver food to grocery stores, enough tellers to wait on customers at banks, and enough telephone repairers to keep the phone system working? A market system solves this problem through two related mechanisms - *changes in wage rates* and the *mobility of labor*.
> **B.E. Kaufman and J.L. Hotchkiss, *The Economics of Labor Markets*, 2006, p. 16.**

> The answers to questions about how people feel toward their job are not meaningless but rather convey useful information about economic life that should not be ignored. [...] Satisfaction is [...] a major determinant of labor market mobility, in part, it is argued, because it reflects aspects of the work place not captured by standard objective variables.
> **R.B. Freeman, *American Economic Review*, 1978, p. 135.**

These quotes illustrate the importance of the interplay of job mobility, wages and job satisfaction for the allocation of labor in a market economy. In trying to reach a better understanding of these phenomena, this thesis presents empirical investigations of the interrelation of job mobility, wages and job satisfaction. These analyses are presented in the chapters 2, 3 and 4, which form part I of the thesis. Part II consists of chapters 5 and 6 presenting two methodological tools that were developed in order to conduct the analyses of part I. They can be understood as technical appendices to the chapters

2 and 3 respectively. The remainder of this introduction summarizes the key findings and conclusions that can be drawn from the thesis.

Although the empirical analyses in part I are based on German data, the results of each chapter are compared to findings from other countries in order to reach an international perspective. Chapter 2 uses data from the German Socio-Economic Panel and takes a specific approach to analyze the association between wages and job mobility. The interest does not lie on wages per se, but on downward wage rigidity. A structural empirical model is estimated, that allows to measure the extent of downward wage rigidity at individual level. This is expressed by the 'wage sweep-up', a measure indicating by how much individual wage growth increases through the effect of downward wage rigidity when compared to a counterfactual labor market with flexible wage setting. In this chapter job mobility is measured by the occurrence of layoffs, quits and intra-firm mobility (promotions and transfers). The findings show robust negative effects of wage sweep-up on quits and layoffs and some evidence for a positive association of wage sweep-up and promotion opportunities. This is consistent with a core-periphery view of the labor force, where a core work force is protected from layoffs and wage cuts and at the same time enjoys good promotion opportunities. On the other side a peripheral work force provides a buffer for adjustment and suffers from both flexible wages, more insecure jobs and less internal promotion opportunities. This finding supports the theory of dual labor markets. According to Rebitzer and Taylor (1991, p. 1373), "dual labor market theory is an attempt to understand observed variation in wages and job quality. The theory argues that market processes tend to produce 'primary' jobs characterized by high wages and long job tenure, and 'contingent' (or 'secondary') jobs that typically offer low wages and short tenure. [...] Primary jobs result from the wage premiums used to elicit high levels of work intensity in firms where the activities of employees are difficult to monitor." According to that theory, a market failure (asymmetric information) is ultimately at the root of a *negative* association of wages and external job mobility.

Chapter 3 takes a different view towards wages and job mobility. Here, only external job mobility is considered. The analysis focuses on the association of wages and job durations. Job durations are a measure of job stability, the counterpart of job mobility. The analysis of that chapter uses German linked employer-employee data. This allows to estimate wage and job duration functions with individual and firm fixed effects. The aim of that analysis is to look into the correlations of the unobserved heterogeneity components. The key finding is that there emerges a trade-off at firm level between wages and job stability: High-wage firms tend to be instable firms, suggesting that job instability is compensated by higher wages. According to the results, high-wage workers sort into the stable low-wage firms, forgoing some of their earnings potential in favor of job stability. Unlike the results of chapter 2, this supports a more market-oriented view of the labor market, in which market forces assure the existence of compensating wage differentials (Rosen 1986).

Taken together, chapters 2 and 3 draw a differentiated picture of the labor market. The results are partly consistent with a standard market model with compensating wage differentials and partly consistent with information asymmetries leading to efficiency wages and dual labor markets. While the analysis of wages is central to labor economics, the question whether wages are really the most important determinant of individual decisions of labor mobility needs to be addressed. Therefore, the analysis of chapters 2 and 3 remains incomplete unless additional non-pecuniary job aspects are added to the analysis. Chapter 4 includes job satisfaction and non-pecuniary job characteristics into the analysis of job mobility. Using the rich data set of the German Socio-Economic Panel, the chapter analyzes the conditions under which low job satisfaction leads to job search, and under which job search leads to job changes. Job satisfaction is not taken as given, but it is itself explained by a set of detailed job characteristics. Individual fixed effects are included into the analysis in order to hold unobserved heterogeneity constant. Non-pecuniary job aspects are found to be very important determinants of job satisfaction. For example, bad relations with colleagues depress job satisfaction so heavily that pay would need to be more than doubled to compensate for this effect. As a wage rise of this extent appears improbable, this implies that a bad atmosphere in the workplace can hardly in practice be compensated by higher wages. Task diversity, conflicts with supervisors, and worries about job security have equally strong effects. The remaining job characteristics also have considerable effects on job satisfaction. Furthermore, job satisfaction is an important determinant of the self-reported probability of job search, which in turn effectively predicts actual job changes. The effect of job search on the probability of job changes varies with job satisfaction and is strongest at low levels of job satisfaction. The effects of job dissatisfaction on job search and of job search on quits are stronger for workers with lower tenure, better educated workers, workers in the private sector and when the economy and labor market are in a good condition. Indeed, this puts the results of the chapters 2 and 3 into perspective. Wages are not the most important determinants of individual job change decisions. The results are of direct importance for employers and human resource managers: firms that do not provide satisfactory working conditions run the risk of experiencing high rates of fluctuation, especially when relying on a highly educated workforce.

The second part of the thesis (chapters 5 and 6) presents two methodological tools that were developed in order to conduct the analyses presented in the empirical part. These tools were made available for public use as Stata programs called `mehetprob` and `felsdvreg`. Chapter 5 is a methodological extension of chapter 2. The effects of wage rigidity on job mobility in chapter 2 are estimated using a heteroskedastic probit model. In such a non-linear regression model, marginal effects need to be computed as non-linear combinations of the regression coefficients. The standard errors of the marginal effects needed for inference and hypothesis testing have to be derived by approximation using methods such as the delta method. In chapter 5, the delta method is applied to derive analytically the standard errors of the marginal effects in a heteroskedastic probit model. Chapter 6 is a methodological extension of chapter 3. The models estimated in chapter 3 are fixed-effects models including two high-dimensional fixed effects (individual and firm effects). A common way to estimate such models is to take into account one of the effects by including dummy variables, and to sweep out the other effect by the within transformation (fixed effects transformation). If the number of groups is high, creating and storing the dummy variables can involve prohibitively large computer memory requirements. In chapter 6, a memory-saving way to estimate a fixed-effects model with two high-dimensional fixed effects is presented. It relies on the idea that a typical dummy variable matrix of fixed effects is a sparse matrix which can be stored efficiently in compressed form.

Part I

Empirical analyses

Chapter 2

Downward wage rigidity and job mobility[1]

Wage rigidity seems to be a defining characteristic of labour markets in many countries. Various studies have investigated wage rigidity and come to the conclusion that wages are not entirely flexible. Especially downward wage rigidity is of relevance, as labour market institutions and fairness standards usually define lower bounds for the wage evolution, not upper bounds. Downward wage rigidity is a potential cause of unemployment and it may distort the allocation of jobs within firms.

We study the effect of downward wage rigidity on mobility decisions in the German labour market. Using data from the German Socio-Economic Panel (GSOEP), we investigate whether being individually affected by wage rigidity affects job mobility. The extent to which an individual is affected by wage rigidity is measured within an empirical model that allows us to estimate the counterfactual wage growth that would prevail in the absence of rigidities.

We distinguish two types of downward wage rigidity: nominal and contractual rigidity. In our empirical model downward *nominal* wage rigidity prevents nominal wage cuts, whereas downward *contractual* wage rigidity prevents wage growth that falls short of the wage growth stipulated by collective wage agreements. Both types of wage rigidity can induce real wage rigidity which is likely to affect the allocation of workers to jobs and hence job mobility. The data set we use contains richer information on labour

[1]This chapter is co-authored with Prof. Dr. Olaf Hübler, Institute of Empirical Economics, Leibniz Universität Hannover. The chapter was originally published as: 'Downward wage rigidity and job mobility', *Empirical Economics*, 34(2), 2008, pp. 205-230. Publication within this thesis with kind permission of Springer Science+Business Media.

market mobility than the data sets that have been used before to measure wage rigidity with this methodological approach. In particular, our data allow us to identify layoffs, quits and intra-firm mobility, namely promotions and transfers.

This chapter is organised as follows. Section 2.1 develops the theoretical background including potential causes of downward wage rigidity and consequences with respect to labour market mobility. On this basis, hypotheses are derived. Section 2.2 presents prior empirical work. Section 2.3 describes our data. Section 2.4 develops the econometric model. Section 2.5 presents results, and section 2.6 concludes. All tables referred to in this chapter can be found in section 2.7.

2.1 Theoretical background

2.1.1 Causes of downward wage rigidity

Theoretical foundations of downward wage rigidity must explain why wages are less responsive to negative shocks than to positive shocks, or in other words: why there is a lower bound to the rate of change of wages. Important theoretical foundations for the existence of lower bounds to the wage evolution are efficiency wage theory, insider-outsider theory as well as theories of efficient contracting.

Fairness standards and reciprocal behaviour induce employers to consider efficiency wages (Akerlof 1982, Akerlof and Yellen 1988, Fehr and Gächter 2000). In order to assess the fairness of their pay, workers compare their wage to some reference wage. If they feel treated in a fair way they offer a high productivity (or low fluctuation) in exchange. In the opposite case workers reciprocate with a low productivity (or high fluctuation). When the reference wage stays relatively constant over the business cycle, firms are likely to avoid wage cuts because the losses in productivity would more than offset the cost savings. Danthine and Kurmann (2004, 2006) show this formally for the two cases where the reference wage is the worker's past wage or the firm's unit wage cost.

Insider-outsider theory maintains that insiders have some bargaining power due to labour turnover costs or labour laws (Lindbeck and Snower 2001). Social norms and fairness standards may also raise bargaining power. Insiders who are protected from layoffs by seniority rules and employment protection legislation may withstand wage cuts in a recession. This prompts layoffs of workers who are not insiders. In a subsequent boom, insiders bargain for wage increases. This lowers the profitability of firms and they do not re-hire formerly laid off workers to the same extent. Over the business cycle, employment is reduced while wages of the employed insiders rise. Bargaining may be mediated by unions. Individual or collective bargaining power makes wage cuts less frequent and wage freezes or wage rises more frequent than they would be in a counterfactual flexible labour market without bargaining power.

Efficient contracting (MacLeod and Malcomson 1993, Holden 1999) has been proposed as a reason for downward nominal wage rigidity (Holden 2002, Elsby 2005). This strand of the literature emphasises that rational agents may chose to apply a fixed nominal wage contract until either side has a credible threat of disrupting trade, in which case renegotiation takes place. The literature argues that fixing the nominal wage in such a way induces efficient investment into specific capital, because it reduces the uncertainty about whether the other party to the contract might capture the rents of the investment. At fixed nominal wages, inflation leads to decreasing real wages and makes upward renegotiation after a positive productivity shock more likely than downward renegotiation after a negative productivity shock. This implies that zero wage growth is frequent, and that wage cuts are comparatively rare as opposed to wage rises.

Zero wage growth may also be an important lower bound to the wage evolution because of fairness standards. For assessing the fairness of the wage set this year, workers take the wage received last year as an important landmark. Other important landmarks are the rate of inflation or the wage growth rate implemented by collective wage agreements (which itself usually depends strongly on the rate of inflation). In our empirical analysis we model two lower bounds for the wage evolution: zero wage growth and collectively bargained wage growth, because a large fraction of the German work force is covered by collective wage agreements. These agreements are usually fixed in nominal terms. They allow to set wages of covered workers above but not below the agreed standard.

To some extent wage rigidity may be efficient. Employers accept certain lower bounds to the wage evolution, because this enhances morale and productivity, reduces fluctuation or encourages investments in specific capital. However, to some extent wage rigidity may be unilaterally enforced through workers' bargaining power without any enhancements of productivity. Employers are likely to oppose to that type of wage rigidity. Pfeiffer (2003) proposes to speak of efficient wage rigidity and bargaining power wage rigidity in order to distinguish these two types of wage rigidity. Indeed, when asked for the reasons of downward wage rigidity, managers in Germany say that not only efficiency wage considerations but also wage floors from collective bargaining are relevant (Franz and Pfeiffer 2003).

2.1.2 The effect of wage rigidity on mobility

In our empirical analysis, the extent of downward wage rigidity at individual level is captured by the wage sweep-up. It measures the excess wage growth due to rigid wages in comparison to a counterfactual labour market with flexible wages. As the wage-employment relationship is central to the economic analysis of the labour market, it is of specific interest to ask how the extent of excess wage growth affects job mobility decisions. We distinguish between external and internal labour mobility. The former comprises quits and layoffs while the latter contains promotions and intra-firm transfers. In the following discussion we formulate hypotheses about whether wage sweep-up increases or decreases job mobility. In the case of layoffs we present two opposing hypothesis, while for the other types of mobility, we restrict the discussion to one hypothesis, conceding that there can also be arguments for the opposite case.

Quits: In search models, quits occur when the discounted utility stream of an alternative job or activity exceeds the discounted utility stream of the current job after mobility costs have been taken into account (Mortensen 1986). Wages as well as non-wage job characteristics are part of the utility associated with a job. To a worker who cares about wages, a high wage sweep-up is an advantage of his current job, as it secures a high wage level and prevents downward wage adjustments in the case of adverse shocks. Ceteris paribus, a high wage sweep-up should therefore reduce the propensity to quit. If an employee interprets the wage sweep-up as a premium to the individual earnings capacity, we should expect that the duration of his search to find a better paid job lasts longer (Gerlach and Hübler 1992) and this means that the probability to quit decreases. Those workers who are not affected by wage sweep-up do not only tend to quit because they feel that they are paid too low compared to other employees in the firm or compared to their effort level, but they may also do so due to a higher anticipated risk of being laid off (see discussion on wage rigidity and layoffs in the next section).

Hypothesis 1: A higher wage sweep-up **reduces** the propensity to quit.

Layoffs: If firms cannot or do not want to cut wages, they need some alternative adjustment mechanism to shocks. Firms may prefer to adjust to negative shocks through layoffs. These do less damage to morale and productivity of the remaining workforce, because the concerned workers exit the firm. Laid off workers suffer and would like to react, but they are no longer in the firm. The threat of layoffs may even increase the productivity of those who stay in the firm (Bewley 1999).

Hypothesis 2a: A higher wage sweep-up **increases** the risk of being laid off.

However, workers are heterogeneous with respect to their degree of wage sweep-up. Whether or not layoffs are positively associated with wage sweep-up at individual level will depend on whether firms lay off workers among those most affected by wage rigidity, or whether firms lay off other groups of workers. If protecting workers from wage cuts is a motivation and incentive device, it may be targeted towards certain groups of workers who are likely to acquire firm-specific human capital and who have a long-term value to the firm. When being forced to lay off personnel, firms are then unlikely to lay off those workers. They may rather lay off other groups of workers. This implies that workers protected against wage cuts or moderate wage growth by rigid wages benefit at the same time from employment security, while other groups of workers simultaneously suffer from higher earnings volatility and greater employment risks. The same is true if, in the case of wage sweep-up due to bargaining power, intended layoffs of high wage sweep-up workers cannot be realised because of employment protection legislation and labour laws. Those insiders that benefit from wage rigidity may also benefit from labour legislation with respect to layoffs. In Germany, firms have to justify layoffs for economic reasons and they are bound to a social plan that stipulates social criteria in order to assess which employees of the work force are actually laid off.

Both explanations correspond to a core-periphery view of the labour force, where a core work force is at the same time protected from layoffs and from wage cuts, whereas a peripheral work force provides a buffer for adjustment and suffers from both flexible wages and more insecure jobs. The resulting hypothesis is the inverse of hypothesis 2a.
Hypothesis 2b: A higher wage sweep-up **reduces** the risk of being laid off.

Another adjustment strategy would be to moderate positive wage growth rates of those workers not directly affected by wage rigidity in order to make up for the excess wage growth of those workers affected. The cost of downward wage adjustments may actually not only reduce wage cuts, but may also make firms more reluctant to grant wage increases, as they know that reversals of wage increases in the future are costly (Elsby 2005). Such a compression of the wage growth distribution would not necessarily reduce employment, although it would distort the allocation of workers of different skills and productivity in comparison with an uncompressed wage growth distribution.

Promotions: Employers might use positional changes to adjust wages when wages within positions are rigid (Solon, Whatley and Stevens 1997). Wage rises are realised through promotions. Wage freezes or moderate wage growth might be implemented by reducing promotion opportunities or even by increasing demotions or transfers. Workers with a high wage sweep-up are less likely to receive a promotion because wage growth in the past had exceeded productivity growth for these workers. They are less productive per unit of wage costs and further promotions are thus unlikely.
Hypothesis 3: A higher wage sweep-up **reduces** the chances of being promoted.

Transfers of personnel: Workers who have accumulated a high wage sweep-up may be transferred to positions where they are more productive relative to their wage level or to positions where wages are less rigid. The old position can then be filled with a worker who can be recruited internally or externally at a lower wage. If the new position exhibits lower or more volatile wage growth, this may also have direct adverse consequences on productivity and therefore it is questionable whether it is a feasible option when efficiency wage considerations are an important factor. A demotion might be as harmful to worker motivation as a wage cut. However, if in the new position efficiency wage considerations are a minor factor (e.g. if output can be monitored more easily or if shirking is less costly) the impact of a transfer on productivity may be less severe than that of a wage cut in the same position. In a setting where wages are rigid primarily due to bargaining power, and thus efficiency wage considerations do not play a role, aspects of motivation are less important. Adverse effects of demotions or transfers on worker productivity are then expected to be small, thus making them a possible strategy to circumvent wage rigidity.

Hypothesis 4: A higher wage sweep-up **increases** the likelihood of being transferred to a different job within the firm.

2.2 Related literature

The earnings function approach we use to measure wage rigidity is pioneered by Altonji and Devereux (2000) who explore downward rigidity in nominal wages for the U.S. They estimate the probability of receiving a nominal wage cut at close to zero and conclude that nominal wage rigidity is a pervasive phenomenon in the U.S. labour market. The earnings function approach has been applied to measure downward nominal wage rigidity in Switzerland (Fehr and Goette 2005), Italy (Devicienti 2002) and Germany (Knoppik and Beissinger 2003)[2]. Downward nominal wage rigidity, which prevents wage cuts, translates into downward real wage rigidity at low rates of inflation[3]. However, downward nominal wage rigidity is not the only reason for downward real wage rigidity, because wages can be rigid at any rate of wage growth. The earnings function approach has therefore been extended by also considering situations where wages cannot be increased by less than a certain rigidity threshold, for example the rate of inflation. When in addition to nominal wage rigidity such a supplementary rigidity threshold is considered, the literature has termed this as modelling 'real wage rigidity', although

[2] Of course a number of other methods have been applied to measure wage rigidity by analysing the features of the wage change distribution in micro data sets. See for example Beissinger and Knoppik (2001) and Christofides and Stengos (2002).

[3] We should mention that Kandil's (2005) empirical investigation demonstrates that prices appear more downwardly rigid than nominal wages in response to demand fluctuations in the U.S. Therefore real wage reductions during economic downturns can be exacerbated. However, demand fluctuations are not the only shocks of relevance for wage growth.

the threshold is not necessarily always equal to the rate of inflation (Bauer, Bonin and Sunde 2003, Devicienti, Maida and Sestito 2003, Barwell and Schweitzer 2005). Fehr, Goette and Pfeiffer 2002 have equalled the rigidity threshold to the collectively bargained wage growth rate and therefore termed the wage rigidity defined by their model as *contractual* wage rigidity. The studies that have extended the earnings function approach in such a way find that a higher share of the work force is affected by real or contractual wage rigidity than by nominal wage rigidity, and that wage growth is swept up more substantially by real or contractual wage rigidity than by nominal wage rigidity.

Several studies that have used the earnings function approach to measure wage rigidity also explore whether an effect of wage rigidity on unemployment and mobility can be established. Fehr and Goette (2005), Bauer, Bonin and Sunde (2003) and Devicienti, Maida and Sestito (2003) find positive associations between wage sweep-up and unemployment. They all study the effects at some level of aggregation. In order to see whether wage rigidity distorts job allocations within firms, however, one has to look at the micro level.

At the micro level, Altonji and Devereux (2000) find modest support for the hypothesis that wage sweep-up reduces quits, but their analysis shows no clear effect of wage sweep-up on layoffs and promotions. Pfeiffer (2003), based on the model estimated in Fehr, Goette and Pfeiffer (2002), finds that wage sweep-up decreases the individual unemployment risk and the incidence of external job changes. While the analysis shows no adverse consequences for those workers affected by wage rigidity, a high wage sweep-up seems to be linked to declining employment at the firm level and to attenuated employment growth at the sectoral level. Pfeiffer (2003, p. 266) therefore concludes that wage rigidity does not have adverse effects on those workers directly affected by the rigidity, but on others whose wages are flexible.

To our knowledge our study is the first to include internal transfers into the analysis of the effects of wage rigidity. For Germany, our analysis is the first to include internal job mobility and to distinguish quits and layoffs exactly instead of proxying them by job changes and unemployment spells. A further contribution of the study is methodological. Under the assumption that rounding is an adequate indicator of measurement error we assign the incidence of measurement error at individual level instead of estimating a global parameter of the probability that observations are affected by measurement error as preceding studies have done (see section 2.4 for details).

2.3 Data

We use data from the German Socio-Economic panel (GSOEP) household survey that contains a rich set of socio-economic variables. Our data cover the period from 1984 – 2004. An overview of the structure of the GSOEP is provided by Haisken-DeNew and Frick (2003).

We restrict our sample to employed workers between 18 and 65 years of age, for whom data on wages is available for at least two consecutive years. Apprentices are excluded. We drop observations where monthly wages are below 250 Euros. The GSOEP states the gross wage including overtime payment, as well as contractual working hours and overtime. The values refer to the month prior to the interview. We construct hourly wages by dividing the monthly gross wage by the sum of monthly contractual hours and overtime. This measures labour costs more appropriately than if only the contractual working hours were considered. Through the variation of overtime work firms may gain some wage flexibility that would not show up in a measure of hourly wages that just accounted for contractual working time.

We capture wage growth by taking the difference in the log wage for all wage observations that are available in two consecutive years. We trim the wage change distribution by dropping observations with absolute wage changes of more than 0.5 log points, thereby removing 4 % of the observations, assuming that such high growth rates are not correctly measured. Besides regressors from the GSOEP, we also match external information to our data set. These are the annual inflation and unemployment rate as well as data on collectively bargained wage growth. The inflation rate is constructed from the consumer price index of the German Federal Statistical Office[4]. Unemployment rates for East and West Germany are published by the German Federal Labour

[4]The consumer price index is available on-line in the "prices" section of the German Federal Statistical Office homepage, http://www.destatis.de/themen/e/thm_preise.htm, link accessed on 30th September 2004.

Office[5]. The index of collectively bargained wages is published by the German Federal Statistical Office[6]. The index is not available for all sectors. Notably the agricultural sector is missing, some parts of the public sector are missing, and, apart from the hotel and restaurants industry, large parts of the service sector are missing. This has to be kept in mind when interpreting our results. Furthermore, for East Germany the index is only available from 1995. When constructing collectively bargained wage growth rates a further year is lost. East German observations thus only enter our analysis from 1996 onwards. Missing values of regressors further reduce the sample size[7]. Finally, from 1984 to 2003 we have 41 626 wage change observations.

The GSOEP survey includes retrospective questions on job mobility. Respondents are asked whether there were any employment changes since the first of January of the preceding year and, if so, which types of changes. We use the response option 'I have started a new position with a different employer' to identify external job mobility and 'I have changed positions within the same company' to identify internal job mobility. External job moves can be further classified through another question that asks how the previous employment relationship was terminated. We use the option 'My resignation' to identify quits and 'Dismissal' to identify layoffs. Internal job moves can be further classified through a question asking respondents to compare their current position with their previous one along several dimensions, including the type of work and the income. In our analysis, promotions qualify as those internal job moves where the worker either states an improved income or an unchanged income alongside improvements in the type

[5] Monthly and yearly unemployment data by region is available at the German Federal Labour Office on-line at http://www.pub.arbeitsamt.de/hst/services/statistik/aktuell/iiia4/zr_alo_qu_west_ostb.xls, link accessed on 25th September 2004.

[6] The data is taken from the German Federal Statistical Office. Up to 2002 the data are from the STATIS CD-ROM time series data base, segments 4031, 4033, 4037, 4039, 4055 and 4057. After 2002 they are updated from the GENESIS online data base of the German Federal Statistical Office. In our sample collectively bargained wage growth is on average 3.1 % with a standard deviation of 1.5 % and a maximum of 11.5 %.

[7] Compared to the whole sample, our estimation sample contains a higher share of male workers (0.66 as opposed to 0.56) which is mostly due to the under sampling of the public and the service sector. Workers in the estimation sample are on average two years older and have two more years of tenure than workers in the whole sample. The distribution of education, firm size and employment status is not altered much by the sample selection.

of work. We regard the remaining internal moves as demotions or transfers. More details on the job mobility variables are presented in Cornelißen/Hübler (2005, appendix A).

The data set has strengths and weaknesses for the present purpose. The benefit from using household survey data is that available regressors are much richer with respect to socio-economic, demographic and work-place related information. While administrative data may provide very accurately measured data on wages, quite often variables of particular interest are missing. For example, comparing the GSOEP survey to the German IAB employment sub-sample (IABS, Beschäftigtenstichprobe), the GSOEP has more detailed information on hours worked, human capital and job mobility. In fact, the IABS lacks information on hours worked. Only the broad categories full- and part-time are reported, and changes between the two within a given year are not registered. Furthermore, earnings data are right censored, as wages are only recorded up to the social security contribution ceiling. This reduces some of the alleged accuracy of the IABS. Job changes and job separations can be identified in the IABS, but the reason for the separation is unknown. In the GSOEP, we can identify quits, layoffs and other separations separately, as well as internal job moves at the same employer. Job mobility being in the focus of our analysis means we would not be able to conduct our analysis with the IABS.

However, by using a household survey as opposed to administrative data we have to cope with two drawbacks. Firstly, household surveys usually provide smaller sample sizes than data sets that are provided by the social security or fiscal administration. Secondly, household surveys are more prone to measurement error than registry data from official sources. This makes the estimation of wage growth rates, that takes place within the structural model presented in the next section, less precise, although it is possible to take measurement error into account when formulating the model.

2.4 The econometric model and estimation issues

We estimate the extent of wage rigidity using the earnings function approach introduced by Altonji and Devereux (2000). This approach models the *observed* wage change through

(i) an underlying *notional* wage change that is the wage change which would prevail in absence of wage rigidity,

(ii) the effect of downward wage rigidity, and

(iii) the effect of measurement error.

The model we use is similar to the one devised by Dickens and Goette (2002), which represents a generalisation of the original Altonji-Devereux model in that it incorporates not only downward nominal wage rigidity but it adds another wage setting regime. As in Fehr, Goette and Pfeiffer (2003), we add a contractually rigid wage setting regime and we use data on collectively bargained wage growth as the rigidity threshold in this regime.

The notional wage change w^*_{it} for individual i at time t depends on a set of covariates x_{it},

$$w^*_{it} = x'_{it}\beta + e_{it}, \qquad e_{it} \sim N(0, \sigma^2_e) \tag{2.1}$$

where β is a coefficient vector and e_{it} the error term.

Whether or not an individual actually receives her notional wage change depends on whether the wage is set in a rigid wage setting regime, and whether wage setting within this regime is constrained or not. There are three wage setting regimes, a flexible, a nominally rigid regime and a contractually rigid regime.

In the **flexible wage setting regime**, the actual wage change of the worker, w^a_{it}, always equals the notional wage change

$$w^a_{it} = x'_{it}\beta + e_{it} \tag{2.2}$$

In the two rigid regimes, the actual wage changes equals the notional wage change only if the notional wage change exceeds a certain threshold value.

Formally, wage setting in the **nominally rigid regime** is then characterised by

$$\begin{aligned} w^a_{it} &= x'_{it}\beta + e_{it} \qquad \text{if } x'_{it}\beta + e_{it} > 0 \\ &= 0 \qquad\qquad\quad\;\; \text{otherwise} \end{aligned} \tag{2.3}$$

and in the **contractually rigid regime** by

$$\begin{aligned} w^a_{it} &= x'_{it}\beta + e_{it} \qquad \text{if } x'_{it}\beta + e_{it} > r_{it} \\ &= r_{it} \qquad\qquad\quad \text{otherwise.} \end{aligned} \tag{2.4}$$

The rigid regimes are tobit models with left censoring of the distribution at the respective rigidity threshold. The variable r_{it} is provided as data in the form of the collectively bargained wage growth. Providing the rigidity threshold as data gives more structure to the estimation and reduces the parameter space. Equalling it to the collectively bargained wage growth takes account of the fact that in Germany a large share of employees is covered by collective bargaining agreements.

The observed wage change is likely to differ from the notional wage change not only because of wage rigidity, but also because of measurement error (misreporting), a problem that is likely to be prevalent in the data set. The observed wage change, w_{it}^o, is then the actual wage, w_{it}^a, change plus measurement error, m_{it}:

$$w_{it}^o = w_{it}^a + m_{it} \qquad m_{it} \sim N(0, \sigma_m^2) \tag{2.5}$$

We assume that m_{it} is independent of e_{it}.

With the measurement error term added to all observations, the three regimes in terms of the observed wage growth become:

$$w_{it}^o = x_{it}'\beta + e_{it} + m_{it} \tag{2.6}$$

for the **flexible wage setting regime**,

$$\begin{aligned} w_{it}^o &= x_{it}'\beta + e_{it} + m_{it} && \text{if } x_{it}'\beta + e_{it} > 0 \\ &= m_{it} && \text{otherwise} \end{aligned} \tag{2.7}$$

for the **nominally rigid regime**, and

$$\begin{aligned} w_{it}^o &= x_{it}'\beta + e_{it} + m_{it} && \text{if } x_{it}'\beta + e_{it} > r_{it} \\ &= r_{it} + m_{it} && \text{otherwise} \end{aligned} \tag{2.8}$$

for the **contractually rigid regime**.

We model a restricted measurement error (Model 1). Instead of adding a measurement error term uniformly to all observations, this is done only for individuals that have reported a rounded value of the wage level in either of two consecutive periods, while treating individuals that have not rounded their wage levels in any of two consecutive periods as error free (i.e. according to equations (2.2)-(2.4)). With this definition 92.9 % of the observations fall into the measurement error regime, the remaining 7.1 % into the regime without measurement error. Under the assumption that rounding is an adequate indicator of measurement error this procedure has the advantage of assigning the measurement error regime at individual level instead of estimating a global parameter of the probability that observations are affected by measurement error. Supplementary, we also estimate a model under the assumption of uniform measurement error (Model 2).

In order to complete the models, we have to account for the individual propensities, p^C, p^N and p^F, of falling into the contractually rigid, nominally rigid and flexible regime respectively. These parameters are made dependent on explanatory variables. We estimate the relative propensities p^C/p^F, and p^N/p^F as

$$\frac{p^C_{it}}{p^F_{it}} = \exp(\tilde{z}'_{it}\lambda), \tag{2.9}$$

and

$$\frac{p^N_{it}}{p^F_{it}} = \exp(\tilde{z}'_{it}\omega), \tag{2.10}$$

where $\tilde{z}_{it}$ is a vector of explanatory variables, λ and ω are the corresponding coefficient vectors. Once the relative propensities are estimated, the absolute propensities p^C, p^F and p^N can be recovered, as (2.9), (2.10) and $p^C + p^N + p^F = 1$ form a system of three linear equations in three unknowns.

The model parameters β, λ, ω, as well as the standard deviations of the error terms, can be estimated simultaneously by maximum likelihood.

Once notional wage growth and the other model parameters are estimated, we can determine expected actual wage growth as well as the wage sweep-up, which is the difference between expected actual wage growth and notional wage growth

$$su = E[w^a_{it} - w^*_{it}]. \tag{2.11}$$

The subsequent analysis of mobility effects consists of heteroskedastic probit regressions of quits, layoffs, promotions and transfers on the wage sweep-up and other control variables. Let y_{it} be a binary outcome variable that takes on the value 1 if job mobility of individual i takes place at time t, and the value 0 if no job mobility takes place. We apply a multiplicative heteroskedastic probit model, where the expected probability of a job mobility event is

$$P(y_{it} = 1) = \Phi\left(\frac{x'_{it}\beta}{\exp(z'_{it}\gamma)}\right), \tag{2.12}$$

where x_{it} and z_{it} are vectors of covariates influencing respectively the mean and standard deviation of the latent variable underlying the probit model, β and γ are the related coefficient vectors, and $\Phi(\cdot)$ is the standard normal cumulative distribution function. Estimated coefficients cannot be readily interpreted as marginal effects. For regressors w_k that are elements of both, x and z, marginal effects of w_k on $P(y_{it} = 1)$ depend on β_k and γ_k as well as on the linear combinations $x'\beta$ and $z'\gamma$ (Greene 2003, p. 680):

$$\frac{\partial \text{Prob}(y = 1|x, z)}{\partial \tilde{w}_k} = \phi \left[\frac{x'\beta}{\exp(z'\gamma)} \right] \frac{\beta_k - x'\beta \cdot \gamma_k}{exp(z'\gamma)}. \tag{2.13}$$

Throughout the analysis of the heteroskedastic probit model, we report marginal effects at means. We derive the respective standard errors needed for inference using the delta method as described in chapter 5.

2.5 Results

2.5.1 Estimates of the wage rigidity model

The tables can be found in section 2.7 (page 27). Table 2.1 reports the maximum likelihood estimation results of the wage rigidity model 1 with restricted measurement error. As a robustness check the estimation under the assumption of uniform measurement error is presented in table 2.6. We report p-values based on robust standard errors as well as on standard errors adjusted for clustering on the year of observation in order to take into account biased estimates of standard errors due to heteroskedasticity and within-group correlation of the error term. The latter may pose a problem in our estimation, as we have matched the unemployment and inflation rates at year level, a procedure which magnifies the bias from within group correlation if such correlation is present (Moulton 1990).

The coefficients of the notional wage growth equation displayed in panel A of Table 2.1 are in line with expectations. The panels B and C of the table report the coefficients of the regime propensity equations. The regime propensities are estimated as nonlinear transformations (see equations 2.9 and 2.10). Therefore, the coefficients cannot be interpreted as marginal effects, but their signs and significance can be assessed.

A positive coefficient on nominal GDP growth for both regime propensities indicates that wage rigidity seems to react cyclically. In upturns, the extent of rigidity rises and in downturns it falls. Firms seem to have more scope to restrain wage growth in recessionary periods. Firms that voluntarily set wages according to collective bargaining agreements may refrain from doing so. Firms covered by union agreements can also moderate the growth of effective wages if they reduce pay components that are not mandatory under the collective contract and thus reduce the 'effective coverage'. With respect to the propensity of the nominal rigid regime, the manufacturing sector seems not to differ from the rest of the economy. The coefficient on the manufacturing dummy is not statistically different from zero. However, the propensity of the contractual regime is significantly lower in manufacturing as compared to the rest of the economy. This can be explained by the important weight of the public sector which dominates the reference group and which is a sector with high union coverage[8].

Panel D of Table 2.1 reports summary statistics for the wage rigidity model. Observed wage growth over the whole period is around 4.1%. The wage growth predicted by the model is 4.3% on average. This is decomposed into a notional wage growth of 0.9 and a wage sweep-up of 3.4%. At individual level the wage sweep-up varies between 1.4 and 6.5%. An estimated 45% of the work force are in the contractually rigid wage setting regime, 2% in the nominally rigid regime, and for 53% wage setting is flexible[9].

Model 2 presented in Table 2.6 predicts a lower notional wage growth of -0.8% and a correspondingly higher wage sweep-up of 4.9% on average. An estimated 32% of the work force are in the contractually rigid wage setting regime, 28% in the nominal rigid regime, and for 40% wage setting is flexible.

Clearly, the way that measurement error is modelled has an effect on the estimated extent of wage rigidity. Although the extent of wage sweep-up differs between the two models, the signs and significance of the determinants in the two models are mostly similar. The wage sweep-ups estimated from the two models are correlated with a highly significant correlation coefficient of 0.96.

[8] In a different specification where we replaced the manufacturing dummy by a public sector dummy, contractual wage rigidity was significantly higher in the public sector than in the reference group.

[9] In a linear regression of the wage sweep-up on worker characteristics and time and sector dummies we find that ceteris paribus wage sweep-up is positively related to nominal GDP growth, that it is higher in East Germany and higher for foreigners, men, high wage workers, more tenured workers, less educated workers and workers in smaller firms (which can be explained by lower notional wage growth in smaller firms).

In essence our results match those of Pfeiffer (2003) in that there is a non negligible extent of wage sweep-up, which is predominantly due to contractual rigidities, and at the same time wage setting is flexible for more than half of the work force. That similar results can be found on the basis of different datasets underlines the robustness of the existence of wage rigidities in the German labour market.
Our results of the extent of wage rigidity are very robust over a range of different specifications of the regime propensities (not reported here), such as the inclusion of the regional unemployment rate, dummies for East German and male workers as well as additional sector dummies, individual tenure and schooling into the regime propensity equations. Even though the extent of wage rigidity was robust, we obtained coefficients on some dummies of a very high magnitude (> 3). This may well be due to the fact that some cells are too sparsely populated. Therefore, and in the vein of a parsimonious specification, we opted for the present model. The results also carry over when the wage rigidity model is estimated in a sample of over 25 year-olds.

2.5.2 The effects of wage rigidity on mobility

In the following analysis, heteroskedastic probit regressions of quits, layoffs, promotions and transfers are presented, where the wage sweep-up and other controls are included as regressors. The timing is such that mobility events between t and *t+1* are explained by labour market regressors at time t. The wage sweep-up at time t, which enters the mobility equations, is based on the wage change observation between *t-1* and t. In all mobility regressions, the heteroskedasticity equation is specified equally and includes key determinants of job mobility, namely the wage sweep-up, the wage level and the number of past external job moves. Tables 2.2, 2.3, 2.4 and 2.5 report the results in terms of marginal effects at means of the regressors on the probability of the mobility events. For those variables that are part of the heteroskedasticity equation, the marginal effect at means can vary in sign. This is due to the functional form of the marginal effects under heteroskedasticity shown in equation (2.13). In the case of the wage sweep-up we therefore also report the fraction of individuals in the sample that display a positive marginal effect of the wage sweep-up.

For each mobility event we estimate four different specifications. Specification (1) is the baseline model which includes the hourly wage level besides the wage sweep-up and a set of control variables. Specification (2) adds the regressors age and age squared. Specification (3) replaces the absolute wage level by the residual of a wage equation ("wage gap"). This is a measure of the individual wage relative to the wage that one would expect given the observable individual characteristics. Such a relative wage measure may be more important for mobility decisions than the absolute wage level, especially in the case of quits.

The wage sweep-up is a complex non-linear interaction of collectively bargained wage growth and of notional wage growth. It is therefore warranted to control for both of these factors in order to isolate the effect of wage rigidity. While many individual characteristics that determine notional wage growth are already included in the control variables, collectively bargained wage growth is not. Specification (4), our preferred specification, therefore adds collectively bargained wage growth as a control variable. All four specifications include the wage sweep-up estimated by model 1. The results can be replicated with the wage sweep-up of model 2, as both wage sweep-ups are nearly perfectly correlated. Table 2.7 presents the results for specification (4) when the wage sweep-up of model 2 is used.

Quits. Table 2.2 reports the probit regression of the quit decision on the wage sweep-up and control variables. The marginal effect at means of the wage sweep-up on the probability to quit is negative and highly significant in all specifications. This suggests that a high wage sweep-up reduces the propensity to quit, as stated in our hypothesis 1. The marginal effect at means is negative for all individuals in the sample. The estimated effects suggest that for an average individual an increase in the wage sweep-up of one percentage point, say from 3% to 4%, reduces the propensity to quit by between 0.54 and 1.56 percentage points. This is a quite sizeable effect if compared to the sample probability of a quit of 3.26%. This is in line with the results of Altonji and Devereux (2000) who find support for the hypothesis that a higher wage sweep-up reduces the propensity to quit. The wage level has no significant effect on quits, but the wage gap reduces the propensity to quit significantly. This implies that not the wage level per se influences quitting but the wage level relative to the wage one can expect given relevant labour market characteristics. Collectively bargained wage growth increases quitting. This may be because favourable collectively bargained wage growth in a given industry indicates good labour market conditions, which in turn encourages job changes. Controlling for this effect increases the negative effect of wage sweep-up on quits. The coefficients of the control variables are in line with expectations.

Layoffs. Table 2.3 reports probit regressions of layoff decisions on the wage sweep-up and control variables. The marginal effect at means of the wage sweep-up on the probability of a layoff is not significant in the baseline specification (1). However, when including age as a regressor in specification (2), the effect of the wage sweep-up on layoffs becomes negative and significant. The wage level significantly reduces layoffs, but the wage gap does not (specification (3)). Specification (4) suggests that the risk of layoffs rises with collectively bargained wage growth. However, layoffs then seem to concern low wage sweep-up workers more than high wage sweep-up workers (and low wage workers more than high wage workers). This finding confirms hypothesis 2b. Individuals with a high wage sweep-up are less likely to be laid off. The marginal effects at means across specifications suggest that an increase in the wage sweep-up of one percentage point reduces the propensity of being laid off by between 0.48 and 1.61 percentage points, which is quite sizeable relative to the sample probability of a layoff of 2.98%. The marginal effect is negative not only for an average individual, but for virtually all individuals in the sample. In the specifications where the effect is significant, at most 2% of the individuals in the sample have a positive predicted marginal effect of the wage sweep-up on layoffs. The coefficients of the control variables are in line with expectations. For those sectors included in our analysis, the negative association between wage sweep-up and layoffs is obtained *holding sectors constant*. Therefore we suppose that it is not due to segregation across sectors, but that it prevails within sectors. However, we can say nothing on whether the negative association is valid within firms, or whether there is segregation across firms. Our results match the findings of Pfeiffer (2003, p. 255ff) that workers with a higher wage sweep-up do not face an increased risk of unemployment and that they have a reduced probability of changing the establishment within the following year.

Promotions. Table 2.4 reports probit regressions of promotions on the wage sweep-up and control variables. The marginal effect at means of the wage sweep-up on the probability of being promoted is negative and significant in specification (1). Once age is controlled for, the effect of the wage sweep-up becomes insignificant (specifications

(2) and (3)). When controlling additionally for collectively bargained wage growth, which is the case in specification (4), the effect of the wage sweep-up on promotions becomes positive and significant and suggests that an increase of the wage sweep-up of one percentage point increases the probability of promotions by 0.34 percentage points. The coefficients of the control variables are in line with expectations. The result that wage sweep-up increases promotion opportunities is the opposite of what we have expected (hypothesis 3). An explanation for this results could be that promotion tournaments, which can be understood as incentive devices (Lazear and Rosen 1981) are a complementary personnel policy to efficiency wages. Both, promotion opportunities and wage rigidity might be combined in order to set incentives and motivate workers.

Transfers. Table 2.5 reports probit regressions of transfers on the wage sweep-up and control variables. As in the case of promotions, the effect of wage sweep-up on transfers is negative and significant in specification (1). Once age is controlled for, the effect becomes positive. However, it stays insignificant across the specifications (2) to (4). Therefore we cannot confirm our hypothesis 4 that transfers are more likely for high wage sweep-up workers. Demotions or transfers might be too damaging to morale and therefore not be an adequate means to cope with rigid wages.

2.6 Conclusion

Using data from the German Socio-Economic Panel (GSOEP), we have analysed the extent of contractual and nominal downward wage rigidity as well as its effect on labour mobility in Germany over the period of 1985-2004.

Within a structural empirical model of wage rigidity, we have estimated that downward wage rigidity increases wage growth by between 3.4 and 4.9 percentage points in the aggregate each year in comparison to a counterfactual labour market with flexible wage setting. We have exploited the variation of this wage sweep-up at individual level in order to estimate probit equations to measure its effect on layoffs, quits, promotions and internal transfers of personnel. According to our results, the effect of the wage sweep-up on quits and layoffs is negative, highly significant and robust across specifications. Wage sweep-up has a strong stabilizing effect on employment relations. The negative association with quits suggests that wage sweep-up constitutes a job specific net advantage. The negative association with layoffs suggests that in the parts of the economy represented by our data there is a dual labour market: A core work force is at the same time protected from layoffs and from wage cuts, whereas a peripheral work force suffers from both, flexible wages and more insecure jobs and provides a buffer for adjustment. However, on the basis of these results for external mobility we cannot discriminate between two concurring explanations: (i) employers aiming at motivating the core work force and tying it to the firm by preventing it from wage cuts and layoffs, or (ii) the core work force being endowed with bargaining power to avoid wage cuts and simultaneously being protected from layoffs by labour legislation or norms.

According to our results for internal job mobility, wage sweep-up seems to go in hand with increased promotion opportunities and there seem to be no effects on transfers and demotions. The duality in the labour market seems to be even stronger than was visible by only considering external mobility. Not only are high wage sweep-up workers protected form layoffs but they also seem to enjoy better promotion opportunities than their low wage sweep-up counterparts. One explanation might be that internal systems of promotions are complementary to efficiency wages. This suggests that the duality in the labour market is to an important extent driven by incentive and motivation considerations and not simply by bargaining power.

We see several perspectives of future research that could extend the present analysis. The model of wage rigidity could be extended by also incorporating symmetric rigidity such as menu costs. Furthermore, it would be worthwhile to implement a model of downward wage rigidity into a data set that allows international comparison, such as the European Community Household Panel (ECHP) an thus to contribute to the empirical literature that has carried out international comparisons in the present field of research (Holden and Wulfsberg 2005, Knoppik and Beissinger 2005, Behr and Pötter 2005). Finally, a model of downward wage rigidity should be implemented in a linked-employer-employee data set, which would allow to model the labour demand side much more extensively by including numerous firm characteristics into the analysis.

2.7 Tables

Tab. 2.1: Wage rigidity model with restricted measurement errors (Model 1)

(A) Notional wage change

	Coeff.[a]	P-val.[b] (i)	P-val.[b] (ii)
Male	−0.45	0.03	0.01
Foreign	−0.28	0.34	0.49
Schooling	−0.08	0.16	0.09
Tenure	−0.24	0.00	0.00
Tenure squared/100	0.51	0.00	0.00
Experience	−0.32	0.00	0.00
Experience squared/100	0.45	0.00	0.00
Months unempl. last year	−0.17	0.50	0.55
Firm size ≥ 20 < 200	0.80	0.01	0.01
Firm size ≥ 200 < 2,000	1.26	0.00	0.00
Firm size > 2,000	1.71	0.00	0.00
Intermediate status group	0.36	0.16	0.19
High status group	1.49	0.00	0.00
Skill training last period	1.23	0.05	0.06
East Germany	0.85	0.29	0.22
South Germany	−0.24	0.23	0.32
Education parents	−0.04	0.66	0.70
Diff. unempl. rate, t	−0.93	0.31	0.40
Diff. unempl. rate, $t-1$	0.38	0.36	0.36
Diff. unempl. rate, $t-2$	−1.31	0.03	0.16
Inflation	−0.79	0.34	0.43
Inflation, $t-1$	1.36	0.00	0.00
Inflation, $t-2$	−0.40	0.52	0.08
Mining	−0.50	0.43	0.51
Manufacturing	0.62	0.06	0.11
Ressource processing	0.09	0.82	0.79
Transp. and communication	−0.39	0.38	0.19
Building sector	−0.31	0.43	0.45
Services	0.45	0.72	0.75
Credit and insurance	−0.01	0.99	0.98
Public utilities	0.00	0.99	0.99
Year 1988	2.98	0.18	0.12
Year 1989	0.10	0.98	0.98
Year 1990	−0.39	0.89	0.90
Year 1991	−0.45	0.91	0.93
Year 1992	2.76	0.49	0.57
Year 1993	0.30	0.92	0.93
Year 1994	−1.89	0.13	0.20
Year 1996	3.11	0.00	0.00
Year 1997	−0.75	0.63	0.60
Year 1998	−3.22	0.02	0.00
Year 1999	−0.60	0.41	0.21
Year 2000	−0.47	0.84	0.86
Year 2001	−2.60	0.31	0.35
Year 2002	−1.31	0.43	0.47
Year 2003	0.41	0.67	0.64
Constant	6.59	0.00	0.00

(B) Relative propensity of nominally rigid regime [log (p^N/p^F)]

	Coeff.	P-val.[b] (i)	P-val.[b] (ii)
Nominal GDP growth	0.56	0.00	0.00
Manufacturing	0.94	0.20	0.39
Constant	−6.66	0.00	0.00

(C) Relative propensity of contractually rigid regime [log (p^C/p^F)]

	Coeff.	P-val.[b] (i)	P-val.[b] (ii)
Nominal GDP growth	0.03	0.00	0.32
Manufacturing	−0.30	0.00	0.00
Constant	−0.21	0.00	0.06

(D) Summary statistics

Wage growth (means)	
Observed	0.041
Predicted	0.043
Notional	0.009
Wage sweep-up	
Mean	0.034
Standard deviation	0.007
5th percentile	0.023
10th percentile	0.025
25th percentile	0.029
50th percentile	0.034
75th percentile	0.039
90th percentile	0.044
95th percentile	0.047
Minimum	0.014
Maximum	0.065
Regime propensities (means)	
p^C	0.45
p^N	0.02
p^F	0.53
Standard errors	
σ_e	0.156
σ_m	0.052
No. of observations	41,626
Log likelihood	23,006.2

[a] All coefficients in panel A are multiplied by 100.

[b] P-Values are based on (i) robust Huber–White sandwich standard errors. (ii) Standard errors adjusted for within group error term correlation, clustering on year

Tab. 2.2: Heteroskedastic probit regression of quits in period $t+1$

	(1)		(2)		(3)		(4)	
No. of observations	38,328		38,328		38,328		38,328	
P-val. Wald test of joint significance[a]	0		0		0		0	
P-val. LR test of heteroskedasticity[b]	0		0		0		0	
Sample probability of $y=1$	3.26%		3.26%		3.26%		3.26%	
Mean predicted probability of $y=1$	3.26%		3.26%		3.26%		3.26%	
Probability of $y=1$ predicted at means	1.48%		1.42%		1.42%		1.46%	
	dP/dX at means	P-val	dP/dX at means	P-val	dP/dX at means	P-val	dP/dX at means	P-val
Wage sweep-up * 100	−1.06%	0.00	−0.54%	0.05	−0.58%	0.04	−1.56%	0.00
Hourly wage level	−0.001%	0.93	0.001%	0.97	–	–	0.001%	0.96
Wage gap (earnings equation residual)	–	–	–	–	−0.12%	0.00	–	–
Collectively bargained wage growth	–	–	–	–	–	–	0.34%	0.01
Age	–	–	0.03%	0.51	−0.02%	0.63	0.15%	0.02
Age squared	–	–	−0.001%	0.15	−0.0002%	0.69	−0.002%	0.01
Fulltime	−0.46%	0.03	−0.50%	0.02	−0.54%	0.01	−0.54%	0.02
East Germany	−0.84%	0.00	−0.84%	0.00	−0.48%	0.00	−0.89%	0.00
Foreign	−0.40%	0.00	−0.43%	0.00	−0.45%	0.00	−0.36%	0.00
Male	0.35%	0.00	0.28%	0.02	0.10%	0.41	0.39%	0.00
Schooling	0.09%	0.00	0.09%	0.00	0.01%	0.64	0.07%	0.02
Number skill trainings	0.06%	0.43	0.05%	0.50	0.03%	0.68	0.01%	0.88
Tenure	−0.15%	0.00	−0.14%	0.00	−0.16%	0.00	−0.12%	0.00
Firm size $\geq 20 < 200$	−0.70%	0.00	−0.58%	0.00	−0.69%	0.00	−0.77%	0.00
Firm size $\geq 200 < 2{,}000$	−0.94%	0.00	−0.79%	0.00	−0.94%	0.00	−1.06%	0.00
Firm size > 2,000	−1.38%	0.00	−1.19%	0.00	−1.41%	0.00	−1.56%	0.00
Number external moves	−0.01%	0.93	−0.01%	0.85	−0.04%	0.62	−0.001%	1.00
Public sector	−0.93%	0.00	−0.90%	0.00	−0.89%	0.00	−0.92%	0.00
Intermediate status group	−0.09%	0.49	−0.08%	0.53	−0.23%	0.07	−0.18%	0.18
High status group	−0.44%	0.02	−0.27%	0.17	−0.80%	0.00	−0.59%	0.01
Fraction with dP/d(sweep-up) > 0	0.00		0.00		0.00		0.00	

All equations include time and sector dummies

[a] H_0: "coefficients jointly insignificant"

[b] H_0: "homoskedasticity" (The heteroskedasticity equation contains the regressors wage level, wage sweep-up, and number of external job moves)

Tab. 2.3: Heteroskedastic probit regression of layoffs in period $t + 1$

	(1)		(2)		(3)		(4)	
No. of observations	38,328		38,328		38,328		38,328	
P-Val. Wald test of joint significance[a]	0		0		0		0	
P-Val. LR test of heteroskedasticity[b]	0.40		0.10		0.07		0.01	
Sample probability of $y = 1$	2.98%		2.98%		2.98%		2.98%	
Mean predicted probability of $y = 1$	2.98%		2.98%		2.98%		2.98%	
Probability of $y = 1$ predicted at means	1.69%		1.64%		1.64%		1.60%	
	dP/dX at means	P-val	dP/dX at means	P-val	dP/dX at means	P-val	dP/dX at means	P-val
Wage sweep-up * 100	−0.21%	0.25	−0.48%	0.04	−0.50%	0.03	−1.61%	0.00
Hourly wage level	−0.11%	0.00	−0.10%	0.00	–	–	−0.10%	0.00
Wage gap (earnings equation residual)	–	–	–	–	−0.03%	0.57	–	–
Collectively bargained wage growth	–	–	–	–	–	–	0.42%	0.00
Age	–	–	−0.17%	0.00	−0.18%	0.00	−0.01%	0.94
Age squared	–	–	0.003%	0.00	0.003%	0.00	0.001%	0.16
Fulltime	−0.03%	0.89	0.06%	0.80	0.05%	0.80	0.06%	0.79
East Germany	1.44%	0.00	1.51%	0.00	1.76%	0.00	1.26%	0.00
Foreign	0.56%	0.00	0.58%	0.00	0.57%	0.00	0.70%	0.00
Male	0.21%	0.15	0.22%	0.12	0.17%	0.30	0.34%	0.01
Schooling	−0.05%	0.14	−0.04%	0.25	−0.06%	0.21	−0.06%	0.09
Number skill trainings	−0.13%	0.20	−0.08%	0.40	−0.09%	0.35	−0.12%	0.22
Tenure	−0.03%	0.02	−0.05%	0.00	−0.05%	0.00	−0.03%	0.02
Firm size $\geq 20 < 200$	−0.64%	0.00	−0.71%	0.00	−0.75%	0.00	−0.89%	0.00
Firm size $\geq 200 < 2{,}000$	−1.10%	0.00	−1.15%	0.00	−1.20%	0.00	−1.38%	0.00
Firm size $> 2{,}000$	−1.48%	0.00	−1.50%	0.00	−1.57%	0.00	−1.82%	0.00
Number external moves	0.23%	0.00	0.23%	0.00	0.22%	0.00	0.19%	0.01
Public sector	−1.26%	0.00	−1.26%	0.00	−1.26%	0.00	−1.21%	0.00
Intermediate status group	−0.46%	0.00	−0.43%	0.01	−0.48%	0.00	−0.52%	0.00
High status group	−0.12%	0.64	−0.26%	0.26	−0.44%	0.21	−0.63%	0.00
Fraction with dP/d(sweep-up) > 0	0.14		0.02		0.02		0.00	

All equations include time and sector dummies

[a] H_0: “coefficients jointly insignificant”

[b] H_0: “homoskedasticity” (The heteroskedasticity equation contains the regressors wage level, wage sweep-up, and number of external job moves)

Tab. 2.4: Heteroskedastic probit regression of promotions in period $t + 1$

	(1)		(2)		(3)		(4)	
No. of observations	36,764		36,764		36,764		36,764	
P-Val. Wald test of joint significance[a]	0		0		0		0	
P-Val. LR test of heteroskedasticity[b]	0		0		0.003		0.001	
Sample probability of $y = 1$	1.38%		1.38%		1.38%		1.38%	
Mean predicted probability of $y = 1$	1.37%		1.38%		1.38%		1.38%	
Probability of $y = 1$ predicted at means	0.68%		0.56%		0.56%		0.55%	
	dP/dX at means	P-val	dP/dX at means	P-val	dP/dX at means	P-val	dP/dX at means	P-val
Wage sweep-up * 100	−0.55%	0.00	0.13%	0.24	0.13%	0.24	0.34%	0.02
Hourly wage level	−0.02%	0.06	−0.02%	0.06	–	–	−0.02%	0.07
Wage gap (earnings equation residual)	–	–	–	–	−0.007%	0.79	–	–
Collectively bargained wage growth	–	–	–	–	–	–	−0.10%	0.05
Age	–	–	−0.06%	0.00	−0.06%	0.00	−0.06%	0.00
Fulltime	0.22%	0.09	0.10%	0.46	0.09%	0.47	0.11%	0.39
East Germany	0.02%	0.86	−0.07%	0.54	−0.04%	0.82	−0.02%	0.85
Foreign	−0.29%	0.00	−0.28%	0.00	−0.28%	0.00	−0.29%	0.00
Male	0.07%	0.41	−0.01%	0.89	−0.02%	0.83	−0.04%	0.61
Schooling	0.09%	0.00	0.10%	0.00	0.10%	0.00	0.10%	0.00
Number skill trainings	0.29%	0.00	0.22%	0.00	0.23%	0.00	0.22%	0.00
Tenure	0.01%	0.20	0.02%	0.00	0.02%	0.00	0.02%	0.01
Firm size $\geq 20 < 200$	0.30%	0.18	0.47%	0.04	0.45%	0.06	0.52%	0.03
Firm size $\geq 200 < 2{,}000$	1.12%	0.00	1.41%	0.00	1.37%	0.00	1.51%	0.00
Firm size > 2,000	1.57%	0.00	1.89%	0.00	1.84%	0.00	2.06%	0.00
Number external moves	0.13%	0.00	0.16%	0.00	0.15%	0.00	0.15%	0.00
Public sector	0.16%	0.32	0.11%	0.40	0.11%	0.41	0.11%	0.41
Intermediate status group	0.15%	0.13	0.12%	0.19	0.10%	0.30	0.13%	0.13
High status group	0.24%	0.21	0.52%	0.02	0.46%	0.16	0.64%	0.01
Fraction with dP/d(sweep-up) > 0	0.00		0.92		0.90		1.00	

All equations include time and sector dummies

[a] H_0: "coefficients jointly insignificant"

[b] H_0: "homoskedasticity" (The heteroskedasticity equation contains the regressors wage level, wage sweep-up, and number of external job moves)

Tab. 2.5: Heteroskedastic probit regression of promotions in period $t + 1$

	(1)		(2)		(3)		(4)	
No. of observations	36,764		36,764		36,764		36,764	
P-Val. Wald test of joint significance[a]	0		0		0		0.001	
P-Val. LR test of heteroskedasticity[b]	0.07		0.20		0.07		0.13	
Sample probability of $y = 1$	0.66%		0.66%		0.66%		0.66%	
Mean predicted probability of $y = 1$	0.66%		0.66%		0.66%		0.66%	
Probability of $y = 1$ predicted at means	0.38%		0.36%		0.36%		0.36%	
	dP/dX at means	P-val	dP/dX at means	P-val	dP/dX at means	P-val	dP/dX at means	P-val
Wage sweep-up * 100	−0.17%	0.03	0.03%	0.73	0.01%	0.92	0.19%	0.11
Hourly wage level	0.01%	0.11	0.01%	0.08	–	–	0.01%	0.10
Wage gap (earnings equation residual)	–	–	–	–	−0.026%	0.33	–	–
Collectively bargained wage growth	–	–	–	–	–	–	−0.08%	0.07
Age	–	–	−0.02%	0.00	−0.02%	0.00	−0.02%	0.00
Fulltime	0.16%	0.05	0.13%	0.12	0.12%	0.16	0.14%	0.10
East Germany	0.13%	0.24	0.10%	0.37	0.22%	0.25	0.14%	0.22
Foreign	0.01%	0.90	−0.0001%	1.00	−0.01%	0.95	−0.01%	0.87
Male	−0.12%	0.09	−0.15%	0.04	−0.18%	0.02	−0.17%	0.02
Schooling	0.06%	0.00	0.06%	0.00	0.05%	0.03	0.06%	0.00
Number skill trainings	0.11%	0.00	0.10%	0.00	0.10%	0.00	0.10%	0.00
Tenure	0.01%	0.16	0.01%	0.03	0.01%	0.14	0.01%	0.13
Firm size $\geq 20 < 200$	−0.001%	0.99	0.04%	0.79	0.00%	0.98	0.07%	0.62
Firm size $\geq 200 < 2{,}000$	0.19%	0.21	0.25%	0.12	0.19%	0.24	0.31%	0.07
Firm size $> 2{,}000$	0.61%	0.00	0.69%	0.00	0.58%	0.01	0.79%	0.00
Number external moves	0.05%	0.04	0.06%	0.01	0.05%	0.03	0.06%	0.01
Public sector	0.11%	0.39	0.10%	0.43	0.08%	0.53	0.10%	0.42
Intermediate status group	0.04%	0.58	0.03%	0.72	0.0003%	1.00	0.04%	0.58
High status group	−0.07%	0.52	−0.02%	0.90	−0.13%	0.36	0.05%	0.74
Fraction with dP/d(sweep-up) > 0	0.01		0.71		0.59		1.00	

All equations include time and sector dummies

[a] H_0: "coefficients jointly insignificant"

[b] H_0: "homoskedasticity" (The heteroskedasticity equation contains the regressors wage level, wage sweep-up, and number of external job moves)

Tab. 2.6: Estimation results of the wage rigidity model with uniform measurement errors (Model 2)

(A) Notional Wage change

	Coeff.[a]	P-val.[b] (i)	(ii)
Male	−0.25	0.30	0.21
Foreign	0.04	0.90	0.93
Schooling	−0.13	0.04	0.02
Tenure	−0.28	0.00	0.00
Tenure squared	0.01	0.00	0.00
Experience	−0.36	0.00	0.00
Experience squared	0.01	0.00	0.00
Months unempl. last year	−0.16	0.57	0.62
Firm size $\geq 20 < 200$	1.00	0.00	0.00
Firm size $\geq 200 < 2{,}000$	1.34	0.00	0.00
Firm size $> 2{,}000$	1.91	0.00	0.00
Intermediate status group	0.37	0.19	0.22
High status group	1.92	0.00	0.00
Skill training last period	1.31	0.06	0.06
East Germany	1.13	0.21	0.16
South Germany	−0.26	0.26	0.37
education parents	−0.09	0.33	0.41
Diff. unempl. rate, t	−1.19	0.24	0.36
Diff. unempl. rate, $t-1$	0.33	0.48	0.51
Diff. unempl. rate, $t-2$	−1.51	0.03	0.16
Inflation	−0.64	0.49	0.58
Inflation, $t-1$	1.59	0.00	0.00
Inflation, $t-2$	−0.68	0.34	0.02
Mining	−0.59	0.40	0.49
Manufacturing	0.89	0.01	0.03
Ressource processing	0.18	0.68	0.65
Transp. and communication	−0.57	0.25	0.10
Building sector	−0.13	0.77	0.78
Services	0.61	0.65	0.69
Credit and insurance	0.07	0.90	0.90
Public utilities	−0.55	0.16	0.20
Year 1988	2.49	0.32	0.28
Year 1989	−1.24	0.75	0.78
Year 1990	−1.75	0.59	0.63
Year 1991	−2.06	0.63	0.72
Year 1992	1.55	0.73	0.79
Year 1993	−0.37	0.91	0.93
Year 1994	−2.18	0.12	0.20
Year 1996	3.50	0.00	0.00
Year 1997	−1.19	0.50	0.48
Year 1998	−3.88	0.01	0.00
Year 1999	−0.94	0.25	0.08
Year 2000	−1.39	0.60	0.67
Year 2001	−3.71	0.20	0.26
Year 2002	−1.82	0.33	0.39
Year 2003	0.33	0.76	0.74
Constant	6.53	0.00	0.00

(B) Relative propensity of nominally rigid regime [log (p^N/p^F)]

	Coeff.	P-val.[b] (i)	(ii)
Nominal GDP growth	0.03	0.13	0.46
Manufacturing	−0.19	0.17	0.19
Constant	−0.43	0.00	0.06

(C) Relative propensity of contractually rigid regime [log (p^C/p^F)]

	Coeff.	P-val. b) (i)	(iii)
Nominal GDP growth	0.09	0.00	0.03
Manufacturing	−0.37	0.00	0.01
Constant	−0.42	0.00	0.11

(D) Summary statistics

Wage growth (means)	
Observed	0.041
Predicted	0.041
Notional	−0.008
Wage sweep-up	
Mean	0.049
Standard deviation	0.010
5th percentile	0.033
10th percentile	0.036
25th percentile	0.042
50th percentile	0.049
75th percentile	0.056
90th percentile	0.063
95th percentile	0.067
Minimum	0.020
Maximum	0.087
Regime propensities (means)	
p^C	0.32
p^N	0.28
p^F	0.40
Standard errors	
σ_e	0.169
σ_m	0.053
No. of observations	41,626
Log likelihood	23,512.1

[a] All coefficients in panel A are multiplied by 100

[b] P-Values are based on (i) Robust Huber–White sandwich standard errors. (ii) Standard errors adjusted for within group error term correlation, clustering on year

Tab. 2.7: Heteroskedastic probit regression of mobility in period $t+1$ based on wage sweep-up of the wage rigidity Model 2

	Quits		Layoffs		Promotions		Transfers	
No. of observations	38,328		38,328		36,764		36,764	
P-Val. Wald test of joint significance[a]	0		0		0		0.000	
P-Val. LR test of heteroskedasticity[b]	0		0.07		0.003		0.09	
Sample probability of $y=1$	3.26%		2.98%		1.38%		0.66%	
Mean predicted probability of $y=1$	3.26%		2.98%		1.38%		0.66%	
Probability of $y=1$ predicted at means	1.45%		1.60%		0.56%		0.36%	
	dP/dX at means	P-val	dP/dX at means	P-val	dP/dX at means	P-val	dP/dX at means	P-val
Wage sweep-up * 100	−1.11%	0.00	−1.04%	0.00	0.24%	0.03	0.11%	0.19
Hourly wage level	0.004%	0.84	−0.10%	0.00	−0.02%	0.05	0.01%	0.08
Collectively bargained wage Growth	0.17%	0.03	0.18%	0.01	−0.07%	0.08	−0.06%	0.15
Age	0.17%	0.01	−0.02%	0.71	−0.06%	0.00	−0.02%	0.00
Fulltime	−0.54%	0.02	0.04%	0.84	0.12%	0.35	0.14%	0.09
East Germany	−0.89%	0.00	1.25%	0.00	−0.02%	0.88	0.15%	0.20
Foreign	−0.47%	0.00	0.51%	0.01	−0.27%	0.00	0.001%	0.99
Male	0.31%	0.01	0.25%	0.07	−0.03%	0.71	−0.16%	0.03
Schooling	0.08%	0.00	−0.04%	0.25	0.10%	0.00	0.06%	0.00
Number skill trainings	0.01%	0.89	−0.11%	0.25	0.23%	0.00	0.10%	0.00
Tenure	−0.11%	0.00	−0.02%	0.08	0.02%	0.02	0.01%	0.14
Firm size $\geq 20 < 200$	−0.82%	0.00	−0.91%	0.00	0.53%	0.03	0.05%	0.71
Firm size $\geq 200 < 2{,}000$	−1.05%	0.00	−1.33%	0.00	1.51%	0.00	0.28%	0.10
Firm size $> 2{,}000$	−1.57%	0.00	−1.79%	0.00	2.08%	0.00	0.75%	0.00
Number external moves	−0.001%	0.99	0.20%	0.01	0.15%	0.00	0.06%	0.01
Public sector	−0.90%	0.00	−1.21%	0.00	0.10%	0.42	0.09%	0.45
Intermediate status group	−0.17%	0.18	−0.50%	0.00	0.13%	0.15	0.04%	0.60
High status group	−0.68%	0.00	−0.65%	0.00	0.68%	0.01	0.04%	0.76
Fraction with dP/d(sweep-up) > 0	0.00		0.00		1.00		0.99	

All equations include time and sector dummies)

[a] H_0: "coefficients jointly insignificant"

[b] H_0: "homoskedasticity" (The heteroskedasticity equation contains the regressors wage level, wage sweep-up, and number of external job moves)

Chapter 3

Why are high-wage workers in low-wage firms? An explanation of a puzzle via job stability and unobserved heterogeneity[1]

Since the availability of linked employer-employee panel data sets empirical labor economists have shown an increased interest in estimating those components of wages that are due to unobserved characteristics of individuals and firms. This literature started with the seminal paper "High wage workers and high wage firms" by Abowd, Kramarz and Margolis (1999) and was followed by several studies for different countries (Abowd, Creecy, Kramarz 2002, Andrews et al. 2008, Alda 2006, Barth and Dale-Olsen 2003, Grütter and Lalive 2004, Goux and Maurin 1999). When analyzing the correlations between the individual and the firm fixed effect from the wage equation, these studies find negative correlations between the two effects. As these fixed effects are often interpreted as reflecting person-specific and firm-specific productivity due to unobserved characteristics (Abowd et al. 2004), that finding implies that the more productive workers sort into the less productive firms. This negative assortative matching has been regarded as a puzzle, because a number of theoretical considerations suggest that one should expect the opposite. When workers and firms are heterogeneous in their productive capacity, the assignment model of Becker (1973) implies positive assortative

[1] This chapter is co-authored with Prof. Dr. Olaf Hübler, Institute of Empirical Economics, Leibniz Universität Hannover. The chapter is a revised version of 'Unobserved Individual and Firm Heterogeneity in Wage and Tenure Functions: Evidence from German Linked Employer-Employee Data', IZA Discussion Paper No. 2741, Bonn 2007.

matching between workers and firms. Abowd et al. (2004) show how Becker's model leads to a positive correlation of the individual and firm effects in a log wage equation.

Different possible explanations for the negative assortative matching have been proposed. These include statistical explanations (Andrews et al. 2008) as well as theoretical explanations. The theoretical explanations rely primarily on job search models (Barth and Dale-Olsen 2003, Shimer 2005, Shimer and Smith 2000, Postel-Vinay and Robin 2002). These existing explanations emphasize individual search behavior but neglect firm behavior. We therefore propose a new explanation for the negative correlation of the individual and firm wage effects, which emphasizes the firms' wage and employment policy. Our approach relies on broadening the scope of the analysis by taking job stability into account and explaining the interaction between wages and job stability. Our main hypothesis is that, due to compensating wage differentials, firms that provide stable jobs can pay lower wages and that high-wage workers can afford to sort into these jobs due to their higher earnings capacity. To test this hypothesis we estimate not only a wage equation but also a job duration equation controlling for worker and firm fixed effects and taking into account the endogeneity of wages and job durations. Subsequently, we analyze the correlations of the individual and firm effects of the job duration equation with those of the wage equation. Our hypothesis implies that we should find a negative correlation between the firm wage effect and the firm job duration effect in evidence of wage differentials compensating for job instability. Furthermore, we should find a positive correlation between the individual wage effect and the firm job duration effect, as workers with a higher earnings capacity are more likely to afford to forgo part of their wages in favor of job stability. This would automatically explain why the individual wage effect and the firm wage effect are negatively correlated. In our empirical results we find these three correlations confirmed as expected and take this as support for our hypothesis.

This analysis adds to the literature in several ways. First, we contribute to the literature on compensating wage differentials that asks whether job insecurity is compensated by higher wages. The results of this literature have thus far been mixed. There are studies that find evidence in favor of compensating differentials (Taubman 1975 and Duncan 1976 for the US, McNabb 1989 for the UK) or estimate a large marginal willingness to pay for job security (Bonhomme and Jolivet 2006 using European data).

Other studies, however, find that job instability or insecurity cause wage concessions instead of compensating differentials (Hübler and Hübler 2006 for Germany and the UK, Carneiro and Portugal 2006 for Portugal) or no significant wage premium for job insecurity (Villanueva 2007 using German panel data).

Second, this study adds to the literature that investigates the determinants of job duration or job mobility controlling for unobserved heterogeneity. We are aware of studies that take into account individual heterogeneity in quit and separations equations using models of binary choice (Anderson and Meyer 1994, Frederiksen 2004, Frederiksen et al. 2007) and of studies that take into account unobserved firm heterogeneity in job duration models (Mumford and Smith 2004, Gerlach and Stephan 2008 and Boockmann and Steffes 2005). To our knowledge, individual and firm effects have not yet been included jointly into a job mobility or job duration equation. However, omitting one or the other is likely to produce biased estimates (Abowd, Kramarz and Margolis 1999).

Third, we add to the literature that takes into account the endogeneity of wages and job durations (Abowd and Kang 2002). Simultaneous wage and mobility equations that account largely for unobserved heterogeneity have been estimated by Abowd, Kramarz and Roux (2006). They find a negative correlation of the intercepts from firm-specific wage and mobility functions ("high-wage firms are low-mobility firms"). This is the opposite finding of our hypothesis stating that firms that provide instable employment have to pay higher wages. They take into account unobserved time-invariant person and firm heterogeneity in the wage equation. However, the mobility equation in Abowd, Kramarz and Roux (2006) considers only firm-specific effects.

We proceed as follows. Section 3.1 develops expectations from a theoretical perspective about the association of individual and firm effects from wage and job duration functions. Section 3.2 describes the data set and discusses the model and the method of estimation. Empirical results follow in section 3.3 and section 3.4 concludes. All tables referred to in this text are to be found in section 3.5. An appendix contains a more detailed description of the estimation samples (section 3.6).

3.1 Theoretical background

In this section we develop hypotheses about the interdependence of individual and firm fixed effects in wage and job duration functions. The fixed effects estimate those components of wages and job durations that are due to unobserved time-invariant individual and firm characteristics. In the subsequent discussion we will refer to "high-wage workers" and "high-wage firms", whereby we mean workers and firms with a high person and firm effect estimated from the wage equation, i.e. workers and firms with unobserved time-invariant characteristics that lead to higher wages. Similarly, when referring to "stable workers" and "stable firms" we mean workers and firms with a high person and firm effect estimated from the job duration equation, i.e. workers and firms with unobserved time-invariant characteristics that lead to higher job durations.

Our main hypothesis concerns the interdependence of the firm job duration effect and the firm wage effect. The starting point of our analysis is that firms differ in their specific level of fluctuation because they face different costs of fluctuation and have different needs of adapting the skill-composition of their work-force. This firm specific level of fluctuation is captured by the firm job duration effect. The firm wage effect, in turn, reflects the firm's wage policy. We concentrate on compensating wage differentials (Rosen 1986) as determinants of the firm wage policy. The theory of compensating wage differentials states that in a competitive labor market undesirable job characteristics are compensated by higher wages. One working condition that ranks as one of the the most important from workers' point of view is job security (Clark 2004). If compensating differentials are operating in the labor market we therefore expect that workers in firms with a higher fluctuation are compensated by higher wages, because their jobs are more insecure. This implies a negative correlation between the firm wage and the firm job duration effect.

Put differently, firms with more stable employment relationships can offer lower wages. This implies that workers can buy job stability by accepting a lower wage. We expect that workers who are better endowed with income will be more likely to buy more job stability, because a higher income generally implies that one can afford more of everything. One way to be better endowed with income is a high individual wage effect, which is commonly interpreted as reflecting a high person-specific productivity.

From this point of view we expect high-wage workers to sort into stable firms and hence a positive correlation between individual wage effect and firm duration effect. According to our hypotheses stable firms are low-wage firms and high-wage workers sort into these firms. It follows that high-wage workers sort into low-wage firms and we expect a negative correlation between individual wage and firm wage effect, which has already been confirmed in different studies (see introduction to this chapter).

We also estimate the association between the individual wage and the individual job duration effect. In line with a frequent interpretation in the literature, we interpret the individual wage effect as reflecting unobserved personal abilities that affect a worker's productivity. We interpret the individual job duration effect as capturing the individual propensity of job stability and mobility. Asking how the individual wage and the individual job duration effect interact therefore means asking how individual abilities are related to the individual propensity of job stability and mobility. It is likely that the effect of unobserved abilities on job stability is similar to the effect of observed abilities, i.e. the level of education. More educated workers may be more mobile because they face a larger job market, search more efficiently and therefore receive more job offers (Mincer 1988). Like education, unobserved abilities may also increase job mobility for the same reasons. On the other hand, employers have an interest to retain workers with higher abilities in the firm. In sum, whether workers with higher abilities are more or less attached to their employer, and hence more or less mobile, is finally an empirical question.

We have no independent theoretical argument for the association of the individual duration effect with the firm wage and the firm duration effect. We consider these associations to be consequences in the sense that once the correlations discussed in this section are known, the sign of the remaining associations should follow logically. Analyzing the signs and significances of the remaining associations is a way to test whether there is an inner logic of our argument and whether the empirical results are consistent.

3.2 Data and empirical method

3.2.1 Data

We use the West German sample of the first version of the longitudinal model of the German linked employer-employee data set LIAB provided by the Institute for Employment Research (IAB)[2]. This data set links the survey data of the IAB establishment panel to employee registry data from the German employment service. A variable list and descriptive statistics of the variables we include into the analysis are provided in Table 3.5 in section 3.5 (page 54). The data cover the whole work force between 1996 and 2002 of the included firms. Out of about 446,000 workers we observe about 2,850 workers in more than one firm (”movers”) in our base sample (Sample 1). The presence of movers is crucial to identify the firm effects.

We use the data to estimate a job duration equation and a wage equation. When referring to the duration of employment spells it is important to distinguish between the elapsed duration and the completed duration. The elapsed duration refers to the duration of a spell that is still ongoing. It can be measured repeatedly, for example each year. This measure of elapsed job duration is included as a regressor on the right hand-side of the wage equation. In the following it is labeled ’tenure’. The completed duration, by contrast, refers to the total length of the employment relationship. It is measured only once, at the moment of separation. It is labeled ’job duration’ in the analysis and constitutes the dependent variable of the the job duration equation, because this is a more adequate measure of job stability than elapsed duration of an ongoing spell. Consequently, we estimate the job duration equation in a sample which contains only one observation per employment relationship (Sample 2). We estimate the wage equation on a different sample than the job duration equation, because it would be inefficient to discard all wage observations of ongoing spells and only retain one observation per employment relationship. The sample for the wage equation therefore includes all observations per employer-employee match capturing the variation of time-varying characteristics during the match (Sample 1).

We restrict our estimations to full-time workers, because there is no information on

[2] Alda et al. (2005) give an overview of the LIAB data set.

the hours worked in the data set and wages of part-timers are therefore not comparable between workers, and for part-timers the information on the job position (blue-collar / white-collar) is missing. The minimum age in our sample is 16 and we base the analysis on employees in regular employment.

Table 3.1 (page 51) gives a numerical overview of the two estimation samples and the appendix (page 56) provides a more detailed description of the samples. In the sample for the wage equation about 446,000 person effects and 740 firm effects are identified. In the sample for the job duration estimation these are about 250,000 person effects and 550 firm effects. After the estimation of the wage and job duration equations in the two samples we have one effect per person and one effect per firm in each sample. As the same persons and firms are in both samples, we can match the wage effects and job duration effects from both samples.

3.2.2 Model and estimation

Our aim is to estimate the determinants of wages and job durations alongside with unobserved individual and firm effects that may be correlated with the observables. We estimate a fixed effects model of the form

$$y = X\beta + D\theta + F\psi + \epsilon, \tag{3.1}$$

where the dependent variable y is either the log wage rate or log job duration[3], X $(N^* \times K)$ is a matrix of time varying characteristics; D $(N^* \times N)$ is a matrix of person dummies capturing the individual effects; and F $(N^* \times J)$ is a matrix of firm dummies capturing the firm effects. By estimating the model as a fixed effects model we allow for an arbitrary correlation between the individual and firm effects and the observed time varying characteristics[4]. N^* is the number of person-years in the data set, J is

[3]Regressing the log duration in a linear model is motivated by the fact that in several duration models (exponential, log-logisitc and lognormal) the logarithm of the duration has linear homoscedastic regression on the explanators (Lancaster 1990, pp. 41, 44, 47).

[4]At this stage we do not include job-match specific effects into the model. However, we apply an instrumental variable estimator that relies on a fixed-effects transformation within job matches (see section 3.2.3). This instrumental variable estimator has been proposed by Altonji and Shakotko (1987) to cope with the endogeneity of a regressor in the presence of match-specific error components. In this sense we take match effects into account.

the number of firms, N is the number of persons, and K is the number of time varying regressors. The coefficient vector β captures the effects of observed time-varying worker and firm characteristics (including time effects). Our main quantities of interest are the unobserved individual effects θ and the unobserved firm effects ψ.

The assumption under which we estimate the model is that the error term is orthogonal to all regressors, including the individual and firm effects. This implies that the matching of workers to firms does not systematically depend on the shocks incorporated in ϵ. We compute the exact least squares solution of this fixed effects model using a memory saving algorithm implemented in a Stata program described in chapter 6. Firm effects are identified through the mobility of workers between firms. Of the 1,904 firms in Sample 1 (see Table 3.1, p. 51), 770 firms have "movers", i.e. workers that are observed in more than one firm of the data set. No firm effects can be estimated for the 1,134 firms without movers. The 770 firms with movers are divided into 30 groups of firms, which are defined such that firms within one group are connected by worker mobility, but firms of different groups are not connected by worker mobility (see Abowd, Creecy and Kramarz (2002) for an algorithm to determine the groups). In each group, one firm effect is not identified and serves as the reference for the remaining effects in the group. In other words, firm effects in one group are only identified relative to each other but not relative to the firm effects of other groups. Therefore, we do not compare person and firm effects between different groups and base our subsequent analysis of the person and firm effects only on effects within groups. In our data we find only one big group (701 firms) and many small groups. For example, the second biggest group has 6 firms and most remaining groups have only 1 or 2 firms. We therefore base the analysis of the person and firm effects only on the biggest of the 30 groups containing the majority of the observations. In Sample 1 these are 88% of the observations[5].

After the estimation of the person and firm fixed effects we can study the correlations of the effects among each other. Under the assumption that individual and firm effects are not correlated with the other regressors, Andrews et al. (2008) and Abowd et al. (2004) show that if $Corr(\theta, \psi)$ is positive, it is actually biased downwards if worker mobility in the dataset is low. With arbitrary correlation between the unobserved het-

[5]That the biggest group contains the majority of observations is a common finding in linked employer-employee data (see Abowd, Creecy and Kramarz 2002 using data from France and the US).

erogeneity and the other regressors, the sign of the bias cannot be determined a priori, but it is an empirical question. The formulae to compute the exact bias when there is arbitrary correlation between unobserved heterogeneity and observed characteristics require the inversion of an $N^* \times N^*$ matrix (Andrews et al. 2008), which is computationally not feasible with the size of our data set. Andrews et al. (2008) propose the alternative of assuming that the observable regressors are uncorrelated with the unobservable heterogeneity. This assumption does not really fit the framework of a fixed effects estimation where one explicitly allows for such correlation. Therefore, we do not compute the bias under this assumption but we use a different finding of Andrews et al. (2008). They show that the bias in the estimation of the correlation decreases if the number of movers increases. We exploit this finding and compute the correlations based on a sub-set of all firm effects that are identified by at least 1, 2, 3, 4 or 5 movers in order to check how the number of movers affects the results. Requiring a number of movers per firm larger than 5 would reduce our sample too much.

3.2.3 Selection of explanatory and instrumental variables

We specify the wage and job duration functions largely with similar regressors. These include age, education, occupational status and profession. Following Munasinghe and Sigman (2004) we construct a variable labeled 'Mobility' that captures the number of past job moves divided by work experience. We also include a number of firm characteristics in the wage and job duration equation. These are firm size, business expectations, investments into IT, the investment sum, the use of fixed-term and part-time work, the application of collective contracts, the existence of a works council, a dummy whether the firm provides training, and the state of the technology used by the firm. Furthermore we include information on a firm's reorganization (insourcing, outsourcing, hiving-off and closure of parts of the firm) and on the structure of the firm's workforce (shares of male and whitecollar workers and mean age of the employees). Firm location is captured by a dummy variable for South Germany, which is economically the strongest region in Germany. The choice of explanatory variables in the job duration equation is comparable to the specifications of the job duration models in Grotheer et al. (2004) and Boockmann and Steffes (2005).

We have to cope with endogeneity in both equations. In the wage equation job tenure is included on the right-hand as an endogenous regressor (Altonji and Shakotko 1987). In the job duration equation, the wage at the moment of separation is included on the right hand side as an endogenous regressor (Abowd and Kang 2002). Endogeneity biases the estimates if the equations are estimated by OLS. Therefore, we employ an instrumental variable (IV) estimator. Job tenure is likely to be an endogenous regressor in the wage equation, because the wage is a determinant of the continuation of the employment relationship. A high wage signals a good job match and is therefore likely to reduce the probability of a separation. However, this endogenous variation of job tenure in the wage equation is variation *between* job matches, not *within* job matches. We therefore follow the proposition of Altonji and Shakotko (1987) who instrument job tenure (T_{it}) by time-demeaned job tenure $T^*_{it} = T_{it} - \bar{T}_s$. Hereby T_{it} denotes job tenure of individual i at time t, and $s = s(i,t)$ indexes the employment relationship of individual i at time t and $\bar{T}_s$ is the average job tenure of that employment relationship. The between-variance (variance between employment relationships s) of the instrumental variable T^*_{it} is zero and endogenous variation in T^*_{it} is therefore minimized. In the job duration equation the wage rate is an endogenous regressor, because in a job spell of longer duration, more specific human capital has been accumulated and the wage is therefore expected to be higher. As an instrument for the wage in the job duration equation we therefore chose the starting wage of the employment relationship, because the starting wage has not yet been influenced by seniority and the accumulation of firm-specific human capital. More specifically, the IV estimator we use is the 2SLS estimator. We include the individual and firm fixed effects in both stages. At the second stage we adjust the standard errors as described in Wooldridge (2002, eq. 5.25, p.95).

3.3 Results

The first three columns of Table 3.2 in section 3.5 (page 52) report the results of the wage equation. Column 1 presents a pooled OLS estimation, column 2 a fixed effects estimation including individual and firm effects, and column 3 the same fixed effects model estimated by the IV estimator described above. This is the preferred specification because it takes into account the endogeneity of job tenure. In this preferred specification, noteworthy results are that firms that provide training seem to pay lower wages, and that firms that employ old technology seem to pay higher wages (column 3 of Table 3.2). In the case of training this may indicate that training predominantly concerns investments into general human capital, which are paid by workers through lower wages. The result that old technology raises wages is only visible in the fixed effects specifications. The fixed effects account for all influences that are time-constant, i.e. that vary only in the cross-section. Fixed effects estimates are therefore more strongly influenced by the longitudinal variation of the regressors than pooled estimates. In order to explain the positive influence of old technology on wages in the fixed effects estimation we therefore need to explain why wages at firm level rise if the firms' technology becomes older. One explanation could be that old technology is correlated with firm age, and firm age influences wages positively. Reasons for a positive influence of firm age on wages may be that unions in older firms are stronger, that older firms are more productive because they have had more time to develop efficient work processes than younger firms, or that the management and the work force are more reluctant against wage cuts or moderate wage growth.

The remaining coefficient estimates are according to expectations. However, comparing the pooled and the fixed effects specifications (columns 1 and 2 of Table 3.2) reveals that considering unobserved individual and firm heterogeneity is important because it has a clear effect on the estimates. For example, the effects of business expectations and of old technology change sign. Furthermore, after including fixed-effects a number of coefficients become insignificant. These concern mostly regressors that exhibit no strong within-firm variation over time, such as dummies for the use of part-time and fixed-term work, information on collective contracts and the existence of the works council, and activities of firm restructuring (outsourcing, hiving-off, insourcing, shut-down part of firm). If the within-firm variance of these regressors is considerably smaller than the total variance, this may lead to lower levels of statistical significance in the fixed-effects regression.

Comparing columns 2 and 3 reveals that taking the endogeneity of job tenure into account has the expected effect of reducing the estimated returns to tenure. The remaining coefficients, however, change only slightly when comparing the fixed-effects IV estimation with the pure fixed-effects estimation.

Columns 4 to 6 of Table 3.2 report the pooled OLS, fixed effects and IV fixed-effects estimations of job durations. Again, the preferred specification is the last one, in which endogeneity of wages is taken into account. In this preferred specification it can be noted that the use of flexible work arrangements (part-time and fixed-term employment), the existence of collective bargaining agreements, and the implementation of firm restructuring (outsourcing, hiving-off, insourcing, shut-down part of firm) in general stabilize employment at firm level. The results also show that firms that provide training and firms that operate with old technology have more instable employment relationships. This matches the findings from the wage equations. Because training is associated with a wage discount in the wage equation, it is likely to concern predominantly investments into general human capital. As general human capital can be transferred to different employers, turnover in firms that provide such training is likely to be higher. The finding from the wage equation that firms whose technology becomes obsolete have higher wages than firms that renew their technology, leads us to expect that these firms have problems to compete in the product market and are finally forced to downward adjustments of their labor force, which can explain the destabilizing effect of old technology on job durations.

The remaining coefficient estimates are according to expectations. Again, a few coefficients in the job durations equation change sign (firm size and share of white-collar workers) and a number of effects lose statistical significance (e.g. variables associated to education and job position, investments, works council, share of male workers) when we move from the pooled estimation to the fixed-effects estimation (from column 4 to column 5 in Table 3.2).

The main purpose of this study is to analyze the correlations of unobserved individual and firm effects estimated from the wage and job duration functions. In Table 3.3 we report partial correlation coefficients holding the observed characteristics age, sex and nationality constant, because the fixed effects absorb the effects of these time-invariant characteristics[6]. The first column of Table 3.3 refers to the correlations of the effects

[6]The variable age can be thought of as being in large parts time-invariant. It can be decomposed into a time-invariant cross-sectional variation between individuals (year of birth) and a variation across time (increase of 1 for each individual each year). In a fixed effects estimation, the cross-sectional variation is absorbed by the fixed-effect and the regressor age becomes indistinguishable form a linear time trend,

computed from the fixed effects IV estimates presented above. In order to compute the correlations we use only firm effects of the biggest mobility group (see section 3.2.2 for the explanation of the mobility groups). Furthermore, we only use firm effects that are identified in both samples (sample for the estimation of the wage equation and sample for the estimation of the job duration equation). As Table 3.4 shows, this leaves us with 487 firms out of 1851 firms. The remaining 487 firms are considerably larger firms than the firms from the total sample, and they also differ in other respects (compare mean values of the variables presented in columns 1 and 2 of Table 3.4). Our results should therefore be interpreted as being representative for large firms. Table 3.4 also shows that restricting the sample to firms with a higher minimum number of movers per firm makes the sample increasingly selective. Therefore, we opt for computing the correlations based on firms with at least one mover as the benchmark case (column 1 of Table 3.3). The remaining columns of Table 3.3 are modifications of the benchmark specification. All correlation coefficients reported in Table 3.3 are highly significant at the 1%-level.

The results can be summarized as follows (the correlations in parentheses are taken from the first column of Table 3.3):

1- High-wage firms are instable firms (-0.05).

2- High-wage workers sort into stable firms (0.08).

3- High-wage workers sort into low-wage firms (-0.31).

4- Stable workers sort into instable firms (-0.55).

5- Stable workers sort into high-wage firms (0.04).

6- High-wage workers are stable workers (0.06).

"High-wage" and "stable" are shortcuts for high wage and high job duration induced by unobserved time-invariant heterogeneity.

which also increases by 1 for each individual each year (Wooldridge 2006, p. 489). Therefore, age cannot be included in a fixed effects regression alongside with a time trend or with a full set of year dummies. Because we include age, one more year dummy than usual is dropped from our estimation.

The first result is consistent with the hypothesis that job instability is compensated by higher wages at the level of the unobserved firm heterogeneity. This implies that workers have the choice to work at somewhat lower wages at a more stable firm, or to work at higher wages at a more instable firm. The second result suggests that workers with unobserved characteristics associated with higher wages are more likely to choose to be employed in the more stable firms. Consequently they accept a wage discount, which is visible in results 3: workers with high individual wage effects are more likely to be employed in low-wage firms. This result is in line with the findings of Alda (2006), Andrews et al. (2008) and Abowd et al. (2002). While it has been regarded as a puzzle in the literature, our results allow for the following explanation: Low-wage firms are more stable firms, hence workers can buy job stability by choosing to work at low-wage firms. Workers that earn higher wages due to good individual characteristics are more likely to afford a wage discount in favor of higher job stability. Results 4 and 5 also fit in. Workers that have individual characteristics that allow them to have stable employment do not depend on choosing a stable firm in order to have a relatively stable employment relationship. They therefore opt for the more instable high-wage firms.

Result 6 states that unobserved individual characteristics that lead to higher wages are related to those unobserved characteristics that lead to more stable employment. This result is somewhat at odds with the previous results. For example, the combination of results 6 and 2 contradicts result 4. This suggests, not surprisingly, that the association between wages and job mobility cannot be explained exclusively by compensating wage differentials. The result shows that to a certain extent employers reward good unobserved characteristics by both, higher wages and more stable jobs, or that employers successfully manage to attach high-ability workers to the firm.

We conduct several robustness checks. First, the results do not depend on whether we include the variable 'Mobility', which captures the number of past job moves divided by work experience, among the regressors. Omitting this regressor does not change the correlations between the effects in any important way[7]. The correlation structure also proved very robust when we changed single regressors or estimated different specifications. For example, we tested a more parsimonious specification of both equations by

[7]The results without the regressor 'Mobility' are available upon request.

leaving out the regressors part-time work, share of male and white-collar workers, mean age and South Germany. This brought about qualitatively the same results as the more comprehensive specification presented here[8].

As it has be shown that the correlation of individual and firm effects from the same equation is biased, and that the bias decreases when the number of movers between firms increases (Andrews et al. 2008, Abowd et al. 2004), we check how the correlations presented in column 1 of Table 3.3 change if we increase our minimum requirement for the number of movers per firm. Columns 2 to 5 report the results if we require a minimum number of 2, 3, 4 and 5 movers per firm. Unfortunately, we cannot increase the minimum number of movers per firm beyond 5, because the number of firms in the sample would shrink too much. Indeed, the correlations between individual and firm effects from the same equation become smaller in absolute value (compare columns 1 and 5 of Table 3.3 for the values of IW-FW and ID-FD), which could be evidence that we have a tendency to overestimate the negative correlation between individual wage and firm wage effects and between individual tenure and firm tenure effects[9]. However, the cross-equation correlations, on which our main results are based, *increase* if we raise the minimum number of movers per firm. Setting this number at 5 movers per firm instead of one mover per firm, the negative correlation between firm wage and firm duration effect increases by a factor of 6, and the positive correlation between individual wage and firm duration effect doubles (compare columns 1 and 5 of Table 3.3 for the values of FW-FD and IW-FD). Hence, our main result that low-wage firms are more stable firms, and that high-wage workers tend to sort into this type of firm gets stronger if we chose 'better' estimates of the unobserved effects by increasing the minimum number

[8]As described in the appendix (section 3.6), there are employment relationships for which we do not observe the completed job duration. Simply dropping all of these spells would not be a satisfactory procedure because it would induce selectivity. We therefore only dropped the ongoing employment relationships of workers with a high expected difference of elapsed and completed job duration (see appendix, section 3.6, for details). Nevertheless we conducted a robustness check by dropping all of these spells. This delivered qualitatively and quantitatively very similar results to the baseline specification (results available upon request).

[9]Andrews et al. (2008) and Abowd et al. (2004) also find that they overestimate the negative correlations between individual wage and firm wage effect, but that the approximate size of the bias is not large enough to turn the negative correlation into a positive one.

of movers required to identify a firm effect.

Columns 6 to 10 of Table 3.3 report how the correlations between the firm and person effects from wage and job duration equations change with varying degrees of control variables. The benchmark specification is again column 1, where we control for both observed and unobserved effects and estimate the wage and duration equation using the IV approach.

Column 6 shows the correlations when we still control for both observed and unobserved effects, but the equations are estimated without taking endogeneity into account. The results of column 6 match closely those of column 1, hence we can say that our results do not depend crucially on using the IV estimator. Column 7 shows the results when we control only for unobserved effects, i.e. we estimate equation (3.1) without X. Here, the previous result that low-wage firms are more stable firms vanishes. This result is only valid after observed firm characteristics have been netted out. Column 8 reports the correlations from estimations that control only for observed effects, i.e. when estimating the person effects we estimate equation (3.1) without F, and when estimating the firm effects we estimate it without D. Here, the result that worker and firm effects from the same equation are negatively correlated vanishes.
In column 9 we repeat the exercise without controlling neither for observed nor for unobserved characteristics. In other words, column 9 reports the correlation of person and firm means of wages and job durations. Here, there appear only positive correlations.

In column 10 we report an estimation that differs from the benchmark specification only in one respect: individual fixed effects are not held constant in the job duration equation when the firm effects of the job duration equation are estimated. The intention is to mimic to some extent the model of Abowd, Kramarz and Roux (2006) who do not control for individual fixed effects in their mobility equation. We do this because our first result, that low-wage firms are stable firms, is not in line with their finding that low-wage firms are high-mobility firms. However, our result of a negative correlation of the firm effects from the wage and the job duration equation carry over also to that specification. The question of why our results deviate from the findings of Abowd, Kramarz and Roux (2006) therefore seems not to be due to the fact that we have introduced controls for individual fixed effects in the mobility equation, but to remaining differences between their study and ours. Remaining differences are that their study is based on data for

France, their mobility equation is modeled by a binary separation indicator, and their observed firm characteristics mainly consist of information on the structure of the work force and on financial indicators of firm performance.

3.4 Conclusion

Our aim was to learn about unobserved individual and firm heterogeneity in wage and job duration functions. We have estimated individual and firm effects that capture time-invariant unobserved heterogeneity in wage and job duration equations and looked into the correlation of the unobserved heterogeneity components with each other.

Our findings apply to unobserved heterogeneity components after netting out the effects of observed heterogeneity. They can be summarised as follows: High-wage workers are more mobile workers. Stable firms are low-wage firms. They seem to ask workers to pay an insurance premium in exchange for job stability. High-wage workers sort into stable firms and thus use their income potential to buy job security. Low-wage workers and stable workers, on the other hand, tend to be matched with the opposite type of firms, i.e. with instable and high-wage firms.

It follows from this sorting mechanism that high-wage workers are employed in low-wage firms. This negative assortative matching, which has also been found in other empirical work, has been regarded as a puzzle. By looking at both, job stability and wages, our explanation of this is that low-wage firms offer job stability, and therefore it is rational for high-wage workers to forgo some of their wage potential by choosing a low-wage firm and thus buying job stability. This implies that even high-ability workers who can relatively easily find new jobs care for job stability. They still want to decide by themselves when to leave a job and not being forced to leave due to employer initiated separations.

3.5 Tables

Tab. 3.1: Overview of estimation samples

Sample:	Sample 1	Sample 2
Estimation of:	Wage equation	Job duration equation
Frequency of observations:	At least yearly	Observation at moment of separation (end of job)
Restriction:	Begin of employment relationship after 1st January 1990.	Begin of employment relationship after 1st January 1990 and right-censored employment spells in 2002 of over 55 year-olds only.
Observations:	1,532,526	295,196
No. Persons:	445,800	250,548
- thereof movers[a]:	2,851	1,423
No. Firms:	1,904	1,849
- thereof with movers	770	594
- mobility groups[b]	30	45
- Identified firm effects[c]	740	549
- Identified firm effects in biggest mobility group	700	487

Notes: *a*) Movers are individuals observed in more than one firm of the sample. *b*) Mobility groups are groups of firms defined such that firms within one group are connected by worker mobility, but firms of different groups are not connected by worker mobility. *c*) In each mobility group 1 firm effect is not identified, because it serves as the reference for the remaining firm effects of that group.

Tab. 3.2: Wage and job duration equations

Dependent Variable	WAGE			JOB DURATION		
	(1)	(2)	(3)	(4)	(5)	(6)
	Pooled OLS	FE	FE, IV	Pooled OLS	FE	FE, IV
N	1532526	1532526	1532526	295196	295196	295196
Tenure	0.022	0.025	0.013			
	(210 .5)	(102 .4)	(32 .5)			
Wage				0.006	0.003	0.005
				(84 .4)	(19 .5)	(22 .4)
Age	0.086	0.118	0.125	0.489	0.536	0.508
	(75 .7)	(43 .6)	(46 .3)	(66 .4)	(8 .1)	(7 .7)
$Age^2/100$	-0.173	-0.226	-0.223	-1.105	-1.192	-1.130
	(-59 .4)	(-32 .7)	(-32 .2)	(-58 .7)	(-7 .2)	(-6 .8)
$Age^3/10{,}000$	0.114	0.141	0.136	0.828	0.907	0.860
	(47 .8)	(25 .0)	(24 .1)	(53 .9)	(6 .9)	(6 .5)
Voc. Training	0.076	0.077	0.078	0.127	0.036	0.032
	(90 .7)	(16 .1)	(16 .4)	(20 .1)	(0 .6)	(0 .5)
Voc. Training and A-levels	0.121	0.086	0.086	-0.101	-0.059	-0.064
	(69 .3)	(9 .3)	(9 .3)	(-7 .6)	(-0 .5)	(-0 .5)
University	0.261	0.171	0.172	0.069	0.140	0.129
	(185 .7)	(18 .9)	(19 .0)	(5 .9)	(1 .0)	(1 .0)
Skilled blue-collar	0.079	0.013	0.015	0.131	0.237	0.237
	(81 .8)	(4 .2)	(4 .8)	(16 .4)	(3 .1)	(3 .1)
White collar	0.154	0.081	0.084	0.123	0.206	0.188
	(94 .6)	(17 .6)	(18 .2)	(9 .6)	(1 .8)	(1 .7)
Log firm size	0.012	0.038	0.037	-0.097	0.738	0.738
	(37 .6)	(14 .9)	(14 .8)	(-37 .9)	(13 .6)	(13 .5)
Business expectations	-0.012	0.010	0.008	0.271	0.488	0.476
	(-4 .7)	(3 .8)	(3 .0)	(11 .3)	(4 .9)	(4 .8)
IT investments (dummy)	-0.007	0.001	0.001	0.501	0.609	0.608
	(-6 .8)	(0 .7)	(0 .7)	(57 .6)	(21 .6)	(21 .5)
Investments (in 10 mill. Euros)	0.001	0.001	0.001	0.007	-0.001	-0.001
	(31 .1)	(17 .3)	(16 .7)	(14 .4)	(-0 .3)	(-0 .3)
Firm uses part-time work	-0.002	-0.0001	-0.0001	0.413	0.602	0.602
	(-1 .3)	(-0 .01)	(-0 .01)	(27 .7)	(12 .1)	(12 .1)
Firm uses fixed-term work	-0.003	0.0001	0.002	0.412	0.604	0.599
	(-3 .0)	(0 .2)	(1 .4)	(47 .4)	(20 .1)	(19 .9)
Sector-level coll. contract	0.018	0.002	0.001	0.148	0.739	0.731
	(11 .2)	(0 .6)	(0 .3)	(12 .1)	(11 .6)	(11 .5)
Firm-level coll. contract	0.032	0.007	0.005	0.056	0.498	0.485
	(17 .2)	(2 .5)	(1 .9)	(3 .8)	(6 .6)	(6 .4)
Works council	0.144	0.003	0.003	0.041	-0.111	-0.112
	(90 .2)	(0 .9)	(0 .9)	(3 .6)	(-1 .3)	(-1 .3)
Firm provides training	0.011	-0.011	-0.010	-0.450	-0.460	-0.455
	(3 .7)	(-2 .8)	(-2 .6)	(-23 .8)	(-6 .2)	(-6 .1)
Old technology	-0.006	0.002	0.002	-0.037	-0.183	-0.180
	(-12 .6)	(2 .9)	(2 .9)	(-9 .8)	(-11 .5)	(-11 .3)
Share males	0.358	0.044	0.038	0.385	0.517	0.491
	(161 .9)	(3 .0)	(2 .6)	(22 .7)	(1 .6)	(1 .5)
Share whitecollar	0.084	0.024	0.025	-0.176	1.427	1.395
	(41 .5)	(2 .5)	(2 .6)	(-11 .2)	(6 .4)	(6 .3)
Mean age	-0.001	-0.008	-0.007	-0.032	-0.264	-0.261
	(-5 .6)	(-21 .8)	(-19 .5)	(-33 .4)	(-37 .7)	(-37 .3)
Mobility	-0.250	-0.067	-0.084	-3.121	-0.540	-0.531
	(-41 .0)	(-7 .1)	(-8 .8)	(-97 .9)	(-5 .6)	(-5 .5)
South Germany	0.006	0.011	0.007	0.036	0.768	0.757
	(8 .6)	(4 .1)	(2 .5)	(7 .1)	(9 .0)	(8 .9)
Outsourcing	-0.009	-0.001	-0.001	0.548	0.557	0.555
	(-7 .0)	(-1 .1)	(-1 .0)	(75 .4)	(22 .7)	(22 .6)
Hiving-Off	0.017	-0.003	-0.001	0.334	0.463	0.455
	(11 .3)	(-2 .1)	(-0 .7)	(33 .6)	(13 .0)	(12 .8)
Insourcing	0.021	0.000	0.000	0.195	0.694	0.690
	(16 .0)	(0 .2)	(0 .1)	(23 .9)	(23 .8)	(23 .6)
Shut-down part of firm	-0.016	-0.002	-0.003	0.519	0.556	0.551
	(-8 .4)	(-1 .2)	(-1 .7)	(52 .0)	(17 .5)	(17 .3)

Note: Year, sector and profession dummies included. T-values in parentheses. Reference categories are: No vocational training, unskilled blue-collar, no collective contract.

Tab. 3.3: Partial correlation of unobserved effects (holding age, sex, nationality constant)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Minimum # movers per firm	>=1	>=2	>=3	>=4	>=5	>=1	>=1	>=1	>=1	>=1
Observed effects included	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	No	Yes
Unobserved effects included	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Partly[a]	Partly[a]	Partly[b]
IV estimation	Yes	Yes	Yes	Yes	Yes	No	No	No	No	Yes
IW - FW	-0.31	-0.26	-0.26	-0.22	-0.20	-0.32	-0.33	0.18	0.26	-0.31
IW - ID	0.06	0.06	0.06	0.04	0.04	0.07	0.13	0.19	0.33	0.06
IW - FD	0.08	0.09	0.11	0.15	0.16	0.08	0.03	0.05	0.15	0.08
ID - FW	0.04	0.03	0.04	0.07	0.11	0.03	-0.04	0.00	0.10	0.04
FW - FD	-0.05	-0.09	-0.15	-0.27	-0.30	-0.04	0.13	-0.27	0.46	-0.09
ID - FD	-0.55	-0.54	-0.53	-0.53	-0.47	-0.55	-0.80	0.47	0.37	0.04
N	59520	54312	48452	44503	39305	59520	59520	59520	59520	59520
# firms	487	325	249	195	155	487	487	487	487	487

IW: individual wage effect, FW: firm wage effect, ID: individual duration effect, FD: firm duration effect; All correlation coefficients reported in the table are statistically significant at the 1%-level; *a*) In column (7) and (8), firm effects are computed without including individual effects and vice versa; *b*) In column (9) firm duration effects are computed without including individual duration effects.

Tab. 3.4: Mean values of firm characteristics in samples with different minimum number of movers per firm

Minimum # movers per firm	>=0	>=1	>=2	>=3	>=4	>=5
# firms	1851	487	325	249	195	155
Log firm size	4.235	5.965	6.455	6.611	6.838	6.947
Sector-level coll. contract	0.758	0.834	0.862	0.876	0.887	0.897
Firm-level coll. contract	0.082	0.090	0.077	0.072	0.077	0.065
Works council	0.549	0.844	0.911	0.932	0.969	0.968
Business expectations	0.002	0.013	0.012	0.010	0.022	0.015
IT investments (dummy)	0.731	0.850	0.862	0.880	0.892	0.890
Investments (in 10 mill. Euros)	0.361	1.033	1.413	1.624	1.732	1.909
Old technology	2.063	2.070	2.058	2.032	2.041	2.045
Firm uses part-time work	0.869	0.947	0.972	0.980	0.990	0.994
Firm uses fixed-term work	0.600	0.850	0.892	0.912	0.933	0.923

Tab. 3.5: Summary statistics

Variable name	Remarks	Sample 1 N=1532526 Mean	S.d.	Sample 2 N=259196 Mean	S.d.	Sample 2c$^{a)}$ N=517709 Mean	S.d.
[t] Job tenure / duration	-	3.88	3.09	2.70	2.87	3.97	3.50
Log tenure / duration	-	0.83	1.29	0.19	1.52	0.75	1.41
Wage	Daily wage	92.45	32.15	80.81	42.20	90.65	38.42
Log wage	-	4.46	0.45	4.23	0.72	4.46	0.51
Censored wage observation	-	0.10	0.30	0.10	0.29	0.12	0.33
Age	-	37.78	9.92	38.21	11.99	38.38	10.55
$Age^2/100$	-	15.26	7.98	16.04	9.90	15.84	8.60
$Age^3/10{,}000$	-	6.55	5.12	7.30	6.56	6.98	5.61
Voc. Training	Dummy: Individual has completed a vocational training / apprenticeship.	0.61	0.49	0.56	0.50	0.59	0.49
Voc. Training and A-levels	Dummy: Individual has completed a vocational training and A-levels ("Abitur").	0.04	0.20	0.04	0.21	0.04	0.21
University	Dummy: Individual has completed a University degree.	0.12	0.33	0.10	0.30	0.12	0.32
Reference: no vocational training and no A-levels and no University degree							
Skilled blue-collar	Individual is in skilled blue-collar job position	0.23	0.42	0.20	0.40	0.22	0.41
White collar	Individual is in whitecollar job position	0.41	0.49	0.40	0.49	0.41	0.49
Reference: unskilled blue collar job position							
Skilled manual	Occupation classification dummies	0.16	0.37	0.14	0.35	0.15	0.36
Technical	-"-	0.11	0.32	0.09	0.28	0.10	0.30
Unskilled services	-"-	0.10	0.30	0.11	0.31	0.10	0.30
Skilled services	-"-	0.02	0.15	0.03	0.16	0.03	0.16
Semi-Professional	-"-	0.04	0.21	0.05	0.23	0.05	0.22
Professional	-"-	0.02	0.14	0.02	0.15	0.02	0.14
Unskilled administrative	-"-	0.05	0.21	0.06	0.23	0.05	0.22
Skilled administrative	-"-	0.16	0.37	0.15	0.36	0.16	0.37
Manager	-"-	0.02	0.14	0.02	0.13	0.02	0.13
Refernce: unskilled manual							
Log firm size	Log no. of workers per firm	7.05	1.48	6.83	1.52	6.98	1.51
Business expectations	Ordinal index of firm's business expectations ranking from -1 to +4.	0.02	0.12	0.01	0.10	0.01	0.09
IT investments (dummy)	Dummy: firm invested into IT	0.88	0.33	0.90	0.30	0.93	0.26
Investments (in 10 mill. Euros)	Firm's investment sum	4.09	8.95	3.04	7.00	3.87	8.07
Firm uses part-time work	Dummy	0.96	0.19	0.97	0.17	0.98	0.15
Firm uses fixed-term work	Dummy	0.86	0.35	0.88	0.33	0.90	0.29
Sector-level coll. contract	Dummy: firm covered by sector-level collective bargaining agreement	0.85	0.35	0.85	0.36	0.85	0.36
Firm-level coll. contract	Dummy: firm covered by firm-level collective bargaining agreement	0.10	0.31	0.10	0.30	0.10	0.30

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Variable name	Remarks	Sample 1 N=1532526 Mean	S.d.	Sample 2 N=259196 Mean	S.d.	Sample 2c$^{a)}$ N=517709 Mean	S.d.
Reference: firm not covered by collective bargaining agreement							
Works council	Dummy: Firm has works council	0.94	0.24	0.91	0.29	0.93	0.26
Firm provides training	Dummy: Firm provides training to its work force	0.95	0.11	0.93	0.13	0.94	0.12
Old technology	Ordinal index of firm's technology coded from 1 (state of the art) to 5 (outdated)	1.98	0.70	1.99	0.69	1.95	0.67
Share males	Share of male workers in firm	0.72	0.24	0.69	0.25	0.70	0.24
Share whitecollar	Share of whitecollar workers in firm	0.35	0.23	0.35	0.24	0.35	0.23
Mean age	Mean age of firm's workers	40.15	2.71	39.93	2.94	40.02	2.78
Mobility	(Number of past job moves divided by years of work experience)*10	0.0013	0.01	0.0022	0.01	0.0016	0.01
South Germany	Dummy: South Germany	0.43	0.49	0.42	0.49	0.42	0.49
Insourcing	Dummy: firm has insourced parts of ist activity	0.06	0.23	0.11	0.31	0.13	0.33
Shut-down part of firm	Dummy: firm has shut down parts of ist activity	0.02	0.16	0.07	0.26	0.07	0.26
Outsourcing	Dummy: firm has outsourced parts of ist activity	0.06	0.24	0.15	0.35	0.17	0.38
Hiving-Off	Dummy: firm has hived off parts of ist activity	0.05	0.22	0.07	0.26	0.10	0.30
Reference: no restructuring of parts of activity							
Year 1997	Dummy	0.11	0.31	0.10	0.30	0.06	0.23
Year 1998	Dummy	0.13	0.33	0.13	0.34	0.08	0.26
Year 1999	Dummy	0.17	0.37	0.17	0.38	0.10	0.30
Year 2000	Dummy	0.17	0.38	0.17	0.37	0.10	0.29
Year 2001	Dummy	0.19	0.39	0.18	0.39	0.10	0.30
Reference: 1996 and 2002 (two year dummies left out because age included in FE regression)							
Agriculture and forrestry	Sector dummy	0.002	0.04	0.003	0.05	0.002	0.05
Mining and energy	-"-	0.02	0.15	0.04	0.19	0.03	0.17
Ressource processing	-"-	0.19	0.39	0.16	0.37	0.17	0.37
Investments goods	-"-	0.39	0.49	0.33	0.47	0.36	0.48
Consumption goods	-"-	0.06	0.23	0.07	0.25	0.06	0.24
Construction	-"-	0.02	0.13	0.03	0.16	0.02	0.14
Retail	-"-	0.04	0.21	0.05	0.22	0.04	0.21
Logistics and Communications	-"-	0.06	0.23	0.05	0.22	0.06	0.23
Credit and banking	-"-	0.03	0.17	0.03	0.16	0.03	0.18
Insurance	-"-	0.01	0.10	0.01	0.11	0.01	0.10
Restauration and hotel	-"-	0.02	0.14	0.02	0.15	0.02	0.14
Education and publishing	-"-	0.03	0.16	0.03	0.18	0.03	0.16
Health sector	-"-	0.07	0.25	0.08	0.28	0.08	0.27
Liberal professions	-"-	0.02	0.13	0.02	0.14	0.02	0.14
Other services	-"-	0.005	0.07	0.01	0.09	0.01	0.07
Reference: Manufacturing							

Note: $^{a)}$ In Sample 2 employment spells that are ongoing in 2002 are dropped for workers younger than 55 years (see explanation in the appendix, section 3.6). In sample 2c no ongoing spells in 2002 are dropped. Summary statistics for sample 2c are presented in this Table for reasons of comparison.

3.6 Appendix: Detailed description of the samples

The employee data consists of employment spells which are generated by mandatory notifications of firms to the German social security authorities. These notifications occur at least once every year (typically at the end of the year). They contain information about who is employed and how much each employee has earned on average since the last notification. The earnings information, however, is reported only up to the social security contribution threshold and we therefore have right-censoring of the earnings variable for about 10% of the wage observations. Apart from the wage, firms also report the education, sex, age, job position, profession, full-time status and other information of each worker (see variable list in Table 3.5 in section 3.5). A typical employment spell of a continuously employed person refers to the time period from the 1st of January to the 31st of December of a given year, but changes in the employment relationship during the year, e.g. change in the full-time status or a change of the health insurance, can generate separate notifications per year and hence separate spells per year in the data.

The job duration variable is constructed from the longitudinal employment information which is available for each employee back to 1990. Completed job duration is measured at the moment of separation (terminations of the employment relationship). We define separations by (i) interruptions of employment with the present employer of longer than 30 days (i.e. the separation is followed by a recall), (ii) changes of the employer identifier (i.e. the separation is followed by a job-to-job move) and (iii) no subsequent employment spell recorded (i.e. the separation is followed by unemployment or inactivity). It follows from our definition of a separation that a worker can have several employment spells with the same employer. About 13% of workers in the data set have experienced a recall[10].

We chose a flow-sampling approach by restricting the estimations to employment relationships that began after the 1st of January 1990. Employment spells that are

[10] Evidence of Mavromaras und Rudolph (1995) based on the same underlying data source, albeit for the time period before 1990, shows that 12% of all newly started employment relationships in Germany are recalls. According to their findings, recalls occur mostly in sectors with seasonal fluctuations, and are more frequent for blue collar workers in the case of men and part-time workers in the case of women.

ongoing in 2002 (end of the observation period) should ideally be treated as censored spells. However, to date there is no model for censored dependent variables that allows to estimate two-way fixed effects. Keeping the ongoing spells without treating them as censored would induce bias because large parts of the analysis would be based on elapsed instead of completed durations. An alternative is to base the analysis only on completed durations. This would cause sample selection, as all ongoing spells in 2002 would be discarded. We aim at minimizing the sample selection by discarding only part of the spells. We only drop the 'worst' spells, i.e. only those spells with a large expected difference between elapsed and completed durations. The expected difference between elapsed and completed duration is higher for younger workers. We therefore only drop the ongoing spells in 2002 of workers younger than 55 years. Table 3.5 in section 3.5 compares the mean values of our estimation sample (Sample 2) to a sample without dropping any censored employment spells (Sample 2c, not used for estimation). The comparison of the mean values of the regressors for Sample 2 and Sample 2c reported in Table 3.5 shows that the main effect of dropping the ongoing spells of workers younger than 55 years is that we have shorter job durations and lower wages in the sample. However, the mean values of person and firm characteristics are similar between the two samples.

In the sample for the wage equation (Sample 1) there is at least one observation per year, but if there are several notifications during a year with changes in wages or explanatory variables, then we keep these as different observations. We could establish an annual panel by keeping just one spell per year. But by doing this we would lose variation in the data and we would lose many short employer-employee matches that last for periods of less than a year. We cannot afford to lose employer-employee matches because they may concern movers and therefore contribute to the identification of firm effects.

Chapter 4

The Interaction of Job Satisfaction, Job Search, and Job Changes - An Empirical Investigation with German Panel Data[1]

This chapter analyses the interdependence of job characteristics, job satisfaction and job changes. I draw on a German household panel data set providing detailed information on job characteristics. Most previous work has analyzed these aspects separately. A number of studies have looked at the determinants of job satisfaction (Warr 1999, Clark 2005, van Praag and Ferrer-i-Carbonel 2004, Addio, Eriksson and Frijters 2004, Böckerman and Ilmakunnas 2006). A key result of these studies is that non-pecuniary job aspects are very important determinants of job satisfaction. Other studies have analyzed the effect of job satisfaction on job mobility (Freeman 1978a, Clark, Georgellis and Sanfey 1998, Akerlof/Rose/Yellen 1988, Clark 2001, Kristensen/Westergard-Nielsen 2004, Lévy-Garboua et al. 2007, Shields/Wheatley Price 2002, Böckerman and Ilmakunnas 2004, Griffeth et al. 2000). These studies have confirmed for different countries that job satisfaction reduces quitting, quit intentions, and job search[2].

[1]This chapter was originally published as: 'The Interaction of Job Satisfaction, Job Search, and Job Changes - An Empirical Investigation with German Panel Data', *The Journal of Happiness Studies*, available online at http://dx.doi.org/10.1007/s10902-008-9094-5. Publication within this thesis with kind permission of Springer Science+Business Media.

[2]Job satisfaction has also been analyzed as a determinant of job changes within the same organization. Delfgaauw (2007) analyzed a Dutch data set and found that dissatisfaction of public sector employees with certain organization-specific job domains increased the probability of leaving the current employer, while dissatisfaction with job aspects that vary sufficiently within an organization can lead to job changes within the organization. However, the present analysis remains confined to job

Currently, there is a lack of studies that combine these strands of the literature by jointly analyzing job characteristics, job satisfaction, job search and job mobility. An exception is a study by Böckerman and Ilmakunnas (2007). Using a Finnish data set, they find that job disamenities reduce job satisfaction, which in turn increases quit intentions and job changes. The existing literature in this context has furthermore neglected to analyze heterogeneous effects. In other words, it has not been analyzed how the effects of job satisfaction on job search, and of job search on job mobility differ according to socioeconomic characteristics, the labor market situation, and the overall economic situation. Previous research has allowed for heterogeneous effects in this context only between men and women (Clark/Georgellis/Sanfey 1998, Clark 2001, Kristensen/Westergard-Nielsen 2004). Moreover, while individual fixed effects have been included in the research on the determinants of job satisfaction (Ferrer-i-Carbonel and Frijters 2004) as well as in studies that analyze job mobility (for example as early as Freeman 1978b), most of the research that has looked at job satisfaction as a determinant of job search and job mobility has employed either pooled regressions or random-effects regressions (Clark et al. 1998, Clark 2001, Kristensen / Westergaard-Nielsen 2004, Lévy-Garboua et al. 2007, Freeman 1978a)[3]. However, Including fixed effects is especially important when subjective data, such as job satisfaction, are analyzed, because it can to some extent alleviate the problem of inter-personal non-comparability of subjective data.

To sum up, the contribution of the present chapter is threefold. First, it checks whether the results by Böckerman and Ilmakunnas (2007) with a Finnish data set can be confirmed for Germany. Second, the analysis adds to the literature by estimating heterogeneous effects of job satisfaction on job search, and of job search on job changes. Third, this chapter pays attention to individual fixed effects in order to investigate how taking into account unobserved heterogeneity affects the answers to the above-mentioned questions.

The chapter is organized as follows. Section 4.1 presents the theoretical considerations and the empirical model. Section 4.2 presents the data and the methodology.

changes to a new employer.

[3]An exception is D'Addio, Eriksson and Frijters (2004), who find that including fixed-effects into the estimation affects the results importantly, and that the random-effects specification is rejected in favor of the fixed effects specification.

Section 4.3 presents results, and section 4.4 contains conclusions. All tables referred to in this chapter are to be found in section 4.5 and section 4.6 contains an appendix with details of the estimation.

4.1 Theoretical considerations and the empirical model

Job satisfaction

As job satisfaction is related to objective job characteristics, it can be viewed as a proxy of on-the-job utility. This utility is likely to depend on pecuniary and non-pecuniary job characteristics. From a theoretical viewpoint, Warr (1999) classified the job-related determinants of job satisfaction into 10 job features, these being personal control, opportunity for skill-use, job demands, variety, environmental clarity (including job security), income, physical security, supportive supervision, interpersonal contact, and a valued social position. The present analysis uses detailed data on job characteristics, which are similar to the dimensions proposed by Warr (1999). Table 4.1 (p. 74) gives an overview of the job characteristics included in the analysis. As a measure of job security, the type of contract is included among the regressors (dummy for a fixed-term contract), because Deloffre and Rioux (2004) have shown that the type of contract is a major determinant of the satisfaction with job security. Furthermore, a subjective measure of job security is also introduced into the analysis (worries about job security). This is useful, because this subjective measure may carry private information about the security of the job not yet captured by the type of contract. Such private information may be the economic situation of the firm or the individual risk of being laid off (Deloffre and Rioux 2004).

Self-reported job satisfaction as a proxy for utility is influenced not only by job outcomes, but also by subjective factors. Satisfaction with job outcomes is determined in an individual reference framework relative to the outcomes of relevant peer groups as well as relative to expectations, aspirations, and values (Warr 1999). Personality traits and other individual unobserved aspects therefore influence self-reported job satisfaction and hence need to be included in the analysis. Some of these subjective factors can be proxied by socio-demographic aspects, such as gender, schooling, age, etc. For example, highly educated workers may have higher aspirations and therefore may on average report lower satisfaction. Socio-demographic characteristics will therefore be included as regressors in the job satisfaction equation. However, not all the individual character traits are observed or can be proxied by observable variables. Furthermore, according to the set point model of happiness, individuals have their own long-run level of well-being, determined by genetic predispositions and personality, around which their well-being fluctuates according to more short-term life circumstances (Diener et al. 1999, Lykken and Tellegen 1996, Myers and Diener 1995). If the unobserved personality traits and genetic predispositions that influence job satisfaction are related to the observed characteristics, estimates of the effect of these characteristics on job satisfaction will be biased. This problem is especially relevant when both the dependent and the independent variable are subjective measures (Hamermesh 2004), because both then include a person-specific effect and the estimates are affected by this effect and do not reveal the true relationship of the underlying objective measures. It is therefore important to account for unobserved individual heterogeneity when estimating job satisfaction equations. Including individual fixed effects in the regression will hold time-invariant unobserved heterogeneity constant. These considerations related to the determinants of job satisfaction lead to the estimation of the following equation:

$$SATIS_{it} = x'_{it}\beta + e_{1i} + u_{1it}, \tag{4.1}$$

where $SATIS_{it}$ denotes job satisfaction of individual i at time t, x_it is the vector of explanatory variables, β is the corresponding vector of regression coefficients, e_{1i} is the individual fixed effect, and u_{1it} is the error term. Besides the job characteristics summarized in table 4.1, the explanatory variables of the job satisfaction equation include the regional unemployment rate, a dummy variable for a public sector job, socioeconomic regressors such as gender, age, years of job tenure, years of education, job position, and a dummy for being new in the job. As further control variables, dummies for year, firm size and sector are included.

Job search

In models of on-the-job search (Mortensen 1986, Mortensen and Pissarides 1999), employed workers engage in job search if the marginal return from searching exceeds its marginal cost. Search effort is adjusted so as to equate the marginal return and the marginal cost of searching. The marginal return increases if the difference between the utility derived from the current job and the expected utility from alternative jobs is high. The lower the utility from the current job (proxied by job satisfaction), the higher is the probability of finding alternative jobs of higher quality, and the higher is the probability of engaging in job search and of choosing a high level of search effort. Search costs, costs of job mobility, the time preference, and the payoff period of a new job (the remaining time up to retirement) also influence job search. From this theoretical framework, the following hypotheses on the effects of job satisfaction and socioeconomic characteristics can be derived. Older people are closer to retirement and have a shorter payoff period in the new job. They are therefore less likely to engage in on-the-job search. Labor market flows are known to respond to cyclical fluctuations. For example, Frederiksen and Westergaard-Nielsen (2007) estimate that an increase in growth in the economy increases flows into new jobs, and Erlinghagen and Knuth (2002) find for Germany that job entry and exit rates are procyclical, i.e. labor mobility is greater during upswings. A good labor market situation (high growth rates and low regional unemployment rates) increases the likelihood of finding good job offers and therefore can be expected to increase the probability of on-the-job search. In downswings, when job vacancies are generally lower, on-the-job search is less likely. However, a poor individual job situation, as opposed to poor labor market conditions in general, is likely to increase job search. The threat of losing one's job is likely to increase on-the-job search. A high individual level of education is likely to affect the chances of receiving outside job offers and makes job search more likely. In the public sector, outside job offers are likely to be less frequent than in the private sector, so that on-the-job search by public sector employees is likely to be lower. Finally, male and female workers may differ in their propensity to engage in on-the-job search. A dummy for gender is therefore also included among the determinants.

Human capital theory (Becker 1962) also provides an important argument for the determinants of job search. The longer an employee has worked for a given employer, the more firm-specific capital he / she has accumulated. Firm-specific capital designates those abilities of the worker that are of value to the current employer but which are of no value to different employers. Firm-specific capital therefore creates a wedge between the wage earned with the current employer and the wage that can be expected with a different employer. From the view of human capital theory, long job tenure makes it less likely that a better-paying job with a different employer can be found and therefore lowers search effort and makes job search less likely.

One of the main aims of this chapter is to investigate how job satisfaction affects the probability of job search differently according to different circumstances. The job search equation accordingly not only includes job tenure, the growth rate of gross domestic product (GDP), the regional unemployment rate, subjective job insecurity, age, education, public sector affiliation, and gender as simple determinants of the probability of job search, but the interaction terms of these variables with job satisfaction are also included. The coefficients of the interaction terms indicate whether the effect of one regressor on the dependent variable depends on the values of another regressor (Wooldridge 2006, p. 204). For example, a negative coefficient for the interaction term of job satisfaction and education would imply that the effect of job satisfaction on job search is more negative (and hence stronger) for highly educated individuals than for less educated individuals.

It is important to control for unobserved heterogeneity in the job mobility regressions. If unobserved heterogeneity is correlated with the observed determinants of job search and job changes, the coefficients of the observed determinants are biased in a pooled regression. For example, there is an ongoing debate on whether the negative effect of tenure on job mobility is due to unobserved heterogeneity in mobility rates (Farber 1999). Self-selection of workers with different intrinsic mobility rates into jobs with different characteristics would lead to biased estimates in the framework of the present analysis. Holding fixed individual effects constant can alleviate these problems.

The job search equation therefore becomes:

$$SEARCH_{it} = \alpha_0 + \alpha_1 SATIS_{i,t-1} + \sum_{j=1}^{l} \gamma_j SATIS_{i,t-1} z_{jit} + c'_{it}\lambda + e_{2i} + u_{2it}, \qquad (4.2)$$

where $SEARCH_{it}$ denotes the self-reported probability of job search of individual i at time t. It is likely that job search influences contemporaneous job satisfaction. Including job satisfaction at time t as a regressor would therefore cause a simultaneity problem[4]. To avoid simultaneity, I include job satisfaction lagged by one period ($SATIS_{i,t-1}$). The vector z_{jit} contains explanatory variables, which are interacted with

[4]Simultaneity arises when an explanatory variable is jointly determined with the dependent variable. Simultaneity biases the estimates of the structural coefficients (Wooldridge 2006, p. 552-555).

job satisfaction. These include gender, job tenure, the German national GDP growth rate, the regional unemployment rate, subjective job insecurity (some or strong worries about job security), age, education, and a dummy for a public sector job. All the regressors z_j that where interacted with job satisfaction are also included in simple form (not interacted) in the regressor vector c_{it}. Besides these variables, c_{it} also includes age and dummies for year, sector, and firm size as control variables. The regression coefficients are α_0, α_1, γ_j $(j = 1 \ldots l)$ and the vector λ, while e_{2i} is the individual fixed effect, and u_{2it} is the error term of the equation.

Job changes

Kristensen and Westergard-Nielsen (2004) have validated empirically that job search is a strong predictor of quits. However, whether job search leads to an actual job changes depends on the circumstances. Of two individuals with the same probability of job search, the one who searches more intensively and who receives better job offers is more likely to change his / her job. Determinants of search effort and of the probability to receive a good job offer should therefore be included. Search effort is likely to be related to job satisfaction and job tenure, whereas the probability of receiving a good job offer is likely to depend on GDP growth, regional unemployment, work experience, education, and public sector affiliation. Hence, these are included as the determinants of job changes. As before, these determinants are included in simple form and as interaction terms, in this case interacted with the probability of job search. Gender is again included as a determinant to capture the different behavior of men and women. Individual fixed effects are also added to the analysis. The job change equation is

$$JOBCHANGE_{it} = \delta_0 + \delta_1 SEARCH_{it} + \sum_{j=1}^{m} \chi_j SEARCH_{it} s_{jit} + t'_{it}\kappa + e_{3i} + u_{3it}, \quad (4.3)$$

where the dependent variable $JOBCHANGE_{it}$ is a dummy variable indicating whether an individual i changes his / her job between period t and *t+1*. Throughout the analysis, only job changes initiated by the employee are considered[5]. The key explanatory

[5] Consequently, quits that lead to unemployment or withdrawals from the labor force are not considered. The reason is that they are not natural outcomes of job search, and job search is central to the analysis. Considering job changes initiated by the employee does not imply that these are voluntary separations. In particular, job changes occurring in anticipation of future job loss can be viewed as involuntary (Manski and Straub 2000).

variables are $SEARCH_{it}$, the self-reported probability of job search, as well as the interaction terms of $SEARCH_{it}$ with other explanatory variables summarized in z_{jit}. These include job satisfaction, gender, job tenure, GDP growth, the regional unemployment rate, years of work experience, years of education, and a dummy for a public sector job. The remaining explanatory variables t_{it} also include these variables in their simple form as well as dummies for year, sector, and firm size as control variables. The regression coefficients are δ_0, δ_1, χ_j $(j = 1 \ldots m)$ and the vector κ, while e_{3i} is the individual fixed effect, and u_{3it} is the error term of the equation.

The detailed job characteristics that are determinants of job satisfaction in equation (4.1) are not included as determinants in the equations (4.2) and (4.3), because I argue that job characteristics influence job search and job changes via utility, and utility is proxied by job satisfaction. Job satisfaction therefore embodies the job aspects that matter according to the preferences and the reference framework of the individual. Equations (4.2)-(4.3) form a system of three regression equations. The appendix in section 4.6 contains details of how this system is estimated.

The present analysis is limited, as not all factors that influence the decision to search for a job or to change a job can be included in the analysis. Omitted factors are satisfaction with the place or location of work, with local community services or with social contacts, and personal events, such as child birth, job changes of spouse, etc. These factors are not included in the model because of data restrictions, and because they are not central to the present analysis of the role of job satisfaction in explaining job search and of how job satisfaction and job search interact in explaining job changes.

4.2 Data

I used data from the German Socio-Economic panel (GSOEP) household survey, which contains a rich set of socioeconomic variables. The data cover the period from 1984 to 2003. An overview of the structure of the GSOEP is provided by Wagner et al. (2007). I restrict the sample to employed West German workers between 16 and 60 years of age.

Job satisfaction of employed respondents is surveyed each year by the question 'How satisfied are you today with your job? Please answer using the following scale [ranging from 0 to 10]: 0 means totally unhappy, 10 means totally happy.' The survey also contained different job characteristics. Some of them, such as wages, work time, and worries about job security are surveyed each year. The more detailed job characteristics, such as task diversity, hard manual labor, relations with colleagues, etc. have been surveyed only in recent years. Table 4.1 gives an overview of the job characteristics included in the analysis and presents the lists of questions associated with each characteristic.

The GSOEP survey also includes several questions about job mobility. In most years, there is a question on the subjective probability of job search. The wording is 'How probable is it in the next two years that you will look for a new job?' The answer to the job search question is coded in 4 integers from 'unlikely' to 'certain'[6]. Furthermore, there are retrospective questions on objective job mobility events. Respondents are asked whether there were any employment changes since 1 January of the preceding year and, if so, what types of change. I use the response option 'I have started a new position with a different employer' to identify job changes. Respondents are also asked how the previous employment relationship was terminated. I use the response 'My resignation' to restrict the job changes to those that are initiated by the employee.

Besides a set of socioeconomic control variables available in the GSOEP, the unemployment rates of the different Federal States and the national GDP growth rate as published by the German Federal Statistical Office are used in the analysis. Matching the unemployment rate at regional level to the micro data can magnify any bias in the estimates of the standard errors if there is within-region correlation of the error term (Moulton 1990). When estimating the job search and the job change equation, standard errors are therefore adjusted for clustering on regions.

For each of the three equations, job satisfaction, job search, and job changes, data are missing in some years, because the information has not been surveyed in each year. The sample sizes and the years on which the estimation of the respective equations are based are indicated in the results tables.

[6] Since 1999, respondents are asked to indicate the probability in percent, choosing between 11 options ranging from 0%, 10%, 20% etc. up to 100%. I harmonize the reply options by recoding 0% as unlikely, 10%-50% as probably not, 60%-90% as probable, and 100% as certain. The recoding is chosen in such a way that in the years before and after the change of the reply options similar fractions of respondents are found in the four categories.

4.3 Results

4.3.1 Descriptive statistics

All tables referred to in this chapter are to be found in section 4.5 (p. 74). Table 4.2 presents the descriptive statistics by gender for 21 job characteristics and overall job satisfaction. According to this report, West German workers seem on average to be satisfied with their jobs. Mean job satisfaction is about 7.3 on the ordinal scale, which ranges from 0 to 10. Judging from the mean of the ordinal job satisfaction variable, men report slightly higher job satisfaction than women, although the difference is small. With respect to the detailed job characteristics, men enjoy higher fringe benefits, more influence, learning and promotion opportunities, a higher task diversity and higher wages. But they also report more worries about job security, being more exposed to environmental risks, hard manual labor, stress, shift work, being more strictly controlled, and longer working hours. For the remaining job characteristics there are only small differences between men and women.

In the following sections, the estimation results of the equations (4.1)-(4.3) are presented. The estimations will first be made without the individual fixed effects, and then fixed effects will be included. When fixed effects are included, the time-invariant characteristics (gender and education) are dropped. Age is also dropped in the fixed-effects estimations, because in a fixed-effects model age is perfectly collinear with the time dummies.

4.3.2 The effects of job characteristics on job satisfaction

Table 4.3 presents the effects of detailed job characteristics on job satisfaction. The first two columns refer to the pooled regressions, and the last column refers to the fixed-effects regression. Comparing the pooled ordered probit regression with the pooled linear regression, all effects are similar in sign and significance. In the present analysis, using a linear model instead of an ordered probit model does not affect the results significantly.

In the pooled regressions most effects of job characteristics on job satisfaction have the expected sign. Fringe benefits, good relations with colleagues, independence, influence, learning opportunities, task diversity, promotion opportunities, wage level, and wage growth increase job satisfaction. Perceived job insecurity, conflict with supervisors, adverse environmental effects, hard manual labor, stress, strict control at work, and a deviation of desired from actual work time reduce job satisfaction. The effects are statistically highly significant and continue to hold in the fixed-effects specification with the exception that hard manual labor is not statistically significant any more. These results are very similar to the results found using Finnish data by Böckerman and Ilmakunnas (2006). They also confirm that physical harm, physically demanding work, the social atmosphere in the workplace, having a voice and the existence of promotion prospect are important determinants of job satisfaction. By comparison with wages, wage growth and fringe benefits, some of the non-pecuniary job characteristics affect job satisfaction extremely strongly. Trade-offs can be computed by comparing the coefficients of different job characteristics. For example, the estimated fixed-effects model (last column of table 4.3) predicts that if the relations with colleagues are not good, a wage rise of 110% is required to maintain the same level of job satisfaction as if relations with colleagues were good[7]. A lack of task diversity, strong worries about job security and conflicts with the supervisor are valued even more highly in terms of wages. The results match Clark's (2005) findings that good relations, job content and other nonpecuniary job aspects have a stronger effect on job satisfaction than income. Similarly, van Praag and Ferrer-i-Carbonel (2004) found that satisfaction with the work itself is more important than pay in determining overall job satisfaction.

In the pooled regression, somewhat counter-intuitively, the effect of shift work on job satisfaction is positive. This effect becomes insignificant once controlled for individual fixed effects. One possible interpretation of the fixed effect in the satisfaction equation is intrinsic satisfaction. For example, the fact that hard manual labor has a negative and statistically significant influence on job satisfaction in a pooled regression but no statistically significant effect in a fixed-effects regression suggests that intrinsically less

[7]In the fixed-effects specification, the coefficient of good relations with colleagues is 0.203, while that on the log wage is 0.275. This implies that the log wage would need to rise by 0.203 / 0.275 = 0.74 log points in order to compensate (hold job satisfaction constant) when relations with colleagues are bad instead of good. A rise of the log wage by 0.74 point is equal to a wage raise of about 110%, as exp(0.74)-1=1.1

satisfied workers seem to work in jobs with hard manual labor. In this context, "intrinsically less satisfied" means that a worker is less satisfied because of a time-invariant characteristic. This may be a subjective characteristic, such as a personality trait, or it may be an objective characteristic, such as the profession a worker works in, insofar as it is unobserved and time-constant.

Some characteristics have no statistically significant effect after holding the large number of job characteristics constant. These insignificant effects include the information whether the activity corresponds to the job that the worker was trained for, whether the job is a fixed-term job, and how long the actual working time is.

According to the effects of the control variables, highly educated workers are less satisfied, which may be explained by their higher aspirations. Male workers are less satisfied, a result which has been previously discussed by Clark (1997). Furthermore, workers seem to be happier with their jobs when unemployment is high, at least in the pooled regression. As their own perceived job security is held constant in the regression, higher regional unemployment means that the relative position of a given worker improves, which can explain higher job satisfaction[8]. In the fixed-effects regression, there emerges a negative and significant effect of job tenure on job satisfaction. In a fixed-effect regression, the coefficient is only identified by the variation of tenure for a given individual, not by the variation of tenure between individuals. The negative effect therefore implies that job satisfaction tends to decrease in a given job. This may reflect a return to the baseline satisfaction as predicted by the set point model of happiness. The result obtained by Böckerman and Ilmakunnas (2006) that job satisfaction rises again after 8 years of job tenure is not confirmed in the dataset used here. Another interesting result is that after holding constant the broad set of job characteristics, there remains no statistical significant effect of being a public sector worker, age, job position, and whether a worker has just moved into a new job.

[8]This result is in contrast to Clark's (2003) finding, with British panel data, that higher unemployment reduces the well-being of employed (and increases the well-being of unemployed) individuals.

4.3.3 The effects of job satisfaction on job search

The subjective probability of job search is an ordinal variable coded in 4 categories (from 'unlikely' to 'certain'). The results of the job search equation (4.2) are presented in Table 4.4. As before, columns 1 and 2 present the pooled ordered probit and pooled linear regression, whereas column 3 presents the fixed-effects regression. The ordered probit regression shows that, as expected, job satisfaction is a strong predictor of job search. High job satisfaction reduces the probability of being in search of a new job. The influence of job satisfaction on job search is stronger for more educated workers, as the respective interaction term has a negative sign and is statistically significant. The influence of job satisfaction on the probability of job search is weaker when job tenure is high, when job insecurity is high, at a higher age, and in the public sector. These influences match the expectations that were discussed in section 4.1. While subjective job security and its interaction with job satisfaction are highly significant, the interaction terms of job satisfaction with the regional unemployment rate and the national GDP growth rate are not statistically significant. One reason may be that the insecurity of a job is much more precisely captured by subjective job security than by aggregate measures such as unemployment and GDP growth rates. A further result is that the effect of satisfaction on job search is not significantly different between men and women.

Comparing the columns 1 and 2 of table 4.4 reveals that the signs and statistical significance of the effects are not much altered when a linear model instead of an ordered probit model is used, with the sole exception of the interaction term of job satisfaction with perceived job insecurity. Including fixed effects into the analysis (column 3 of table 4.4) leaves most of the results unchanged. However, the interaction effect of job satisfaction and education becomes insignificant.

4.3.4 The effects of job search on job changes

Table 4.5 reports the estimation of equation (4.3). In all three specifications presented in the table, a higher subjective probability of job search is associated with a higher probability of changing jobs, as was hypothesized in section 4.1. However, the remaining effects differ quite substantially in some cases between the nonlinear probit model and the pooled linear model (columns 1 and 2 of the table). The most frequent difference is that effects are not significant in the probit model but become significant in the linear model. This is true of the interaction terms of job search with GDP growth, the regional unemployment rate, and the public sector, as well as for the regional unemployment rate and job satisfaction as regressors on their own. In the following, I interpret the results of the linear probability model, but it should be kept in mind that some of these results are not robust against employing the nonlinear probit model and should therefore be interpreted with caution.

With these reservations, the results of the pooled linear probability model suggest that the effect of job search on actual job changes is stronger when workers are more dissatisfied. Higher dissatisfaction hence increases search effort and raises the chances of finding a new job. However, job satisfaction as a regressor in simple form (not interacted with job search) increases job changes[9]. Job satisfaction may increase job changes, because more satisfied people (holding search effort constant) give a better impression in job interviews and are therefore more likely to get a job. This interpretation is supported by empirical results from personnel psychology that show a link between success at job interviews and personality traits such as extraversion, self-esteem, etc. (Liden, Martin and Parsons 1993, Caldwell and Burger 1998, Cook, Vance and Spector 2000), and a correlation of these personality traits with subjective well-being (Hayes and Joseph 2002, Emmons and Diener 1985). The findings of the present analysis suggest that the strong negative effects of job satisfaction on quitting identified by Clark, Georgellis and Sanfey (1998) in data of the same source as used here is actually no direct effect but an indirect effect running via job search activities.

The results of the pooled linear probability model also suggest that the effect of job search on actual job changes is stronger when tenure is short, when GDP growth is high, when regional unemployment is low, when workers are better educated, and

[9] As the previous analysis has shown, there is a strong association between job search and job satisfaction. Including both variables in the job change regression might potentially cause multicollinearity. I therefore also repeated the estimation excluding job satisfaction as a regressor from the job change equation (results available upon request). The magnitudes of coefficients, significance levels and the variance inflation factors computed after the linear regression were very similar. Multicollinearity due to the job satisfaction variable therefore does not seem to be harmful to the present regression.

when workers are employed in the private sector. These results carry over to the fixed-effects regression. Some of the remaining regressors at first sight have counter-intuitive signs in the linear pooled and fixed-effects regressions. For example, GDP growth as a regressor on its own (not interacted with job search) decreases job changes, education as a regressor on its own decreases job changes, and public sector affiliation as a regressor on its own increases job changes. These regressors therefore seem to exert their expected effects on job changes through their interaction with search, but taken on their own, they show opposite effects. For some of these opposite effects, there are plausible explanations: Better economic conditions (GDP growth) may not only improve the job-finding rate, but also improve the future expectations with the present employer, for example, regarding future promotions or wage rises and may therefore affect job changes negatively. If they search more, better educated people have higher probabilities of changing their jobs, because they may be more efficient in searching and are faced with more job opportunities. However, when job search and job satisfaction are held constant, they are apparently more attached to their present employer, probably because they have better opportunities of making a career with their present employer, and because employers put more effort into attaching highly educated workers to the firm than lower educated workers.

4.4 Conclusion

Using German panel data, this chapter has analyzed the effects of detailed job characteristics on job satisfaction as well as the conditions under which low job satisfaction leads to job search, and under which job search leads to job changes. In sum, the results of Böckerman and Ilmakunnas (2007) for Finland can be confirmed also for Germany: adverse job characteristics decrease job satisfaction, which in turn increases job search, which is an important predictor of actual job changes.

From a practical standpoint the results imply that firms that do not provide satisfactory working conditions run the risk of experiencing high rates of fluctuation. Non-pecuniary job aspects are found to be very important determinants of job satisfaction. For example, bad relations with colleagues depress job satisfaction so heavily that pay would need to be more than doubled to compensate for this effect. As a wage rise of this extent appears improbable, this implies that a bad atmosphere in the workplace can hardly in practice be compensated by higher wages. Task diversity, conflicts with supervisors, and worries about job security have equally strong effects. The remaining job characteristics analyzed also have considerable effects on job satisfaction.

The analysis has also shown that job satisfaction is a strong determinant of the probability of engaging in on-the-job search. The more an employee is dissatisfied, the more likely he / she is to search for a new job. This effect is stronger for workers with lower tenure, young workers and workers in the private sector. According to the results of pooled probit regressions, job security (a proxy for a good economic situation) leads to a stronger effect of dissatisfaction on search, but this result is not robust when a linear model is used and fixed effects are included in the analysis.

Finally, job search is found to be an important determinant of the probability of actually changing jobs. Job satisfaction modifies this relationship: at low levels of job satisfaction, the effect of job search on the probability of changing jobs is stronger. This can be interpreted in the way that dissatisfaction increases not only the probability of searching for a job but also the search effort. However, after holding the probability of search and the search effort constant, job satisfaction was found to increase the probability of changing jobs. This seems to show that more satisfied people fare better in job interviews. The results also show that job search is more likely to lead to job changes when workers are employed in the private sector, when job tenure is low, economic conditions are good, and education is high. Especially those firms that rely on a highly educated workforce should therefore worry about the risk of high turnover due to unsatisfactory working conditions.

There remains scope for further research. As the analysis in this chapter is based on household survey data, it was possible to include firm characteristics only by introducing firm size and sector as control variables. Furthermore, job security was not available as an objective piece of information at firm level but was only available as a subjective variable at individual level and as a highly aggregated variable at regional or national level. Further research into this topic should therefore aim at using linked employer-employee data providing much more detailed firm-level information. However, in Germany linked employer-employee data sets currently include neither job satisfaction nor detailed characteristics of individual jobs.

4.5 Tables

Tab. 4.1: Overview of job characteristics

Variable	Surveyed	Wording
Activity corresponds to job	(A)	Is [your] position the same as the profession for which you were educated or trained?
Fringe benefits	(A)	Did you receive any of the following additional payments from your employer last year? (13th month salary, 14th month salary, Additional Christmas bonus, Vacation pay, Profit-sharing, premiums, bonuses, Other or ‘No, I received none of these’.)
		What is your attitude towards your job security - are you concerned about it?
Some worries about job security	(A)	Somewhat concerned
Strong worries about job security	(A)	Very concerned
Fixed-term contract	(A)	Is your contract of employment for an unlimited or limited period?
		I would like to know more about work and the conditions at your place of employment. Please answer the following questions by stating whether it applies to your work completely, partly or not at all.
Conflicts, difficulties with supervisor	(B)	Do you often have conflicts and difficulties with your boss?
Exposed to adverse environment	(B)	Are you exposed to undesirable working conditions (cold, heat, wetness, chemicals, gases)?
Get along well with colleagues	(B)	Do you get along well with your colleagues?
Hard manual labor	(B)	Do you have to do hard manual labor at your job?
Stress	(B)	Does your work involve a high level of stress?
Independence	(C)	Do you decide yourself how to complete the tasks involved in your work?
Influence on pay and promotion of others	(C)	Do you have an influence in determining whether employees receive more pay or promotion?
Learning opportunities	(C)	Do you often learn something new on the job, something which is relevant for your career?
Shift work	(C)	Do you work the night shift or another type of special shift?
Strict control of performance	(C)	Is your work strictly monitored?
Task diversity	(C)	Is your job varied?
Subjective probability of promotion	(B)	How likely is it that the following career change will take place in your life within the next two years: receive a promotion at your current place of employment? Please estimate the probability of such a change according to a scale from 0 to 100.
Deviation of actual from desired work time	(D)	Difference of desired actual work time. Desired work time is taken from the question “If you could choose your own number of working hours, taking into account that your income would change according to the number of hours: How many hours would you want to work?”
Actual work time	(A)	How many hours do your actual working-hours consist of including possible over-time?
Logarithm of net wage	(A)	How high was your income from employment last month? If you received extra income such as vacation pay or back pay, please do not include this. Please do include overtime pay. Fill in your net income, which means the sum after deduction of taxes, social security, and unemployment and health insurance.
Wage growth rate	(A)	=Logarithm of net wage [t] − Logarithm of net wage [t − 1]

(A) Yearly; (B) 1985, 1987, 1989, 1991 to 1994, 1996, 1998, 1999, 2001, 2003, 2005; (C) 1985, 1987, 1989, 1995, 2001; (D) yearly, except 1996

Tab. 4.2: Descriptive statistics of job characteristics

Variable	Unit of measurement	Female	Male	Total			
		Mean	Mean	Mean	Std. Dev.	Min	Max
Job satisfaction	(d)	7.29	7.33	7.31	1.94	0	10
Activity corresponds to job	(a)	0.65	0.63	0.63	0.48	0	1
Fringe benefits	(a)	0.92	0.95	0.94	0.24	0	1
Some worries about job security	(a)	0.05	0.04	0.04	0.20	0	1
Strong worries about job security	(a)	0.29	0.33	0.31	0.46	0	1
Fixed-term contract	(a)	0.06	0.08	0.07	0.26	0	1
Conflicts, difficulties with supervisor	(a)	0.02	0.03	0.03	0.16	0	1
Exposed to adverse environment	(a)	0.07	0.22	0.17	0.37	0	1
Get along well with colleagues	(a)	0.80	0.79	0.80	0.40	0	1
Hard manual labor	(a)	0.09	0.14	0.12	0.32	0	1
Stress	(a)	0.27	0.31	0.30	0.46	0	1
Independence	(a)	0.39	0.40	0.40	0.49	0	1
Influence on pay and promotion of others	(c)	0.13	0.26	0.21	0.41	0	1
Learning opportunities	(a)	0.32	0.38	0.36	0.48	0	1
Shift work	(c)	0.14	0.20	0.18	0.38	0	1
Strict control of performance	(c)	0.45	0.52	0.50	0.50	0	1
Task diversity	(a)	0.58	0.67	0.64	0.48	0	1
Subjective probability of promotion	(b)	0.12	0.21	0.18	0.38	0	1
Deviation of actual from desired work time	Weekly hours	6.35	6.24	6.28	7.63	0	70
Actual work time	Weekly hours	34.66	43.36	40.14	9.90	1.00	80.00
Logarithm of net wage	Log monthly wage	6.75	7.31	7.11	0.52	5.00	9.07
Wage growth rate	Diff. log wage	0.07	0.05	0.06	0.21	−2.15	2.40

$N = 11{,}294$

(a) Fraction saying the job characteristic applies to their job

(b) Coded from 1 = unlikely to 4 = certain

(c) Fraction saying the job characteristic applies or partly applies to their job

(d) Coded in integers from 0 = totally unhappy to 10 = totally happy

Tab. 4.3: Job satisfaction regressions

Model	Pooled ordered probit	Pooled linear (a)	Fixed-effects linear (a)
Activity corresponds to job	0.008 (0.023)	0.008 (0.021)	−0.002 (0.040)
Fringe benefits	0.192*** (0.042)	0.179*** (0.039)	0.161** (0.065)
Some worries about job security	−0.275*** (0.023)	−0.256*** (0.021)	−0.183*** (0.031)
Strong worries about job security	−0.536*** (0.040)	−0.507*** (0.038)	−0.301*** (0.055)
Fixed-term contract	0.020 (0.050)	0.019 (0.046)	0.027 (0.075)
Conflicts with supervisor	−0.820*** (0.061)	−0.785*** (0.056)	−0.484*** (0.076)
Exposed to adverse environment	−0.103*** (0.030)	−0.096*** (0.028)	−0.119*** (0.042)
Good relation with colleagues	0.357*** (0.024)	0.337*** (0.023)	0.203*** (0.032)
Hard manual labor	−0.151*** (0.034)	−0.143*** (0.031)	−0.040 (0.048)
Stress	−0.252*** (0.023)	−0.236*** (0.021)	−0.167*** (0.032)
Independence	0.149*** (0.022)	0.136*** (0.020)	0.124*** (0.028)
Influence	0.095*** (0.027)	0.088*** (0.025)	0.135*** (0.038)
Learning opportunities	0.208*** (0.023)	0.193*** (0.021)	0.126*** (0.029)
Shift work	0.069** (0.028)	0.061** (0.026)	−0.050 (0.049)
Strict control of performance	−0.123*** (0.021)	−0.113*** (0.019)	−0.162*** (0.027)
Task diversity	0.360*** (0.022)	0.336*** (0.021)	0.231*** (0.030)
Subj. probability of promotion	0.115*** (0.027)	0.106*** (0.025)	0.105*** (0.033)
Deviation of actual from desired work time	−0.011*** (0.001)	−0.010*** (0.001)	−0.006*** (0.002)
Actual work time	−0.002 (0.001)	−0.001 (0.001)	−0.002 (0.002)
Logarithm of net wage	0.139*** (0.035)	0.128*** (0.033)	0.275*** (0.066)
Wage growth rate	0.143*** (0.047)	0.131*** (0.044)	0.181*** (0.061)
Regional unemployment rate	0.009** (0.004)	0.008** (0.004)	0.006 (0.014)
Public sector	0.045 (0.034)	0.042 (0.032)	−0.071 (0.066)
Gender: male	−0.056** (0.027)	−0.050** (0.025)	
Age	−0.007 (0.008)	−0.007 (0.008)	
Age squared/100	0.009 (0.010)	0.009 (0.010)	−0.011 (0.016)
Years of job tenure	−0.003 (0.004)	−0.002 (0.004)	−0.016*** (0.006)
Job tenure squared/100	0.001 (0.011)	−0.0001 (0.010)	0.015 (0.018)
Years of education	−0.035*** (0.005)	−0.032*** (0.005)	
Intermediate job position	−0.035 (0.029)	−0.033 (0.027)	0.071 (0.045)
High job position	−0.003 (0.044)	−0.001 (0.041)	0.036 (0.065)
Job move last year	0.058 (0.038)	0.052 (0.035)	0.063 (0.045)
Constant	–	0.018 (0.338)	−1.632** (0.712)
R^2	–	0.179	–
N	11,294	11,294	11,294

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, standard errors clustered on regions in parentheses

Year, sector, and firm size dummies included

Data: GSOEP 1985, 1987, 1989, 1995, 2001

(a) Dependent variable “cardinalized” as described in Appendix A1

Tab. 4.4: Job search regressions

Model	Pooled ordered probit	Pooled linear (a)	Fixed-effects linear (a)
Lagged job satisfaction	−0.157*** (0.017)	−0.139*** (0.011)	−0.095*** (0.020)
Lagged satisfaction × male	−0.008 (0.007)	−0.005 (0.004)	−0.004 (0.005)
Lagged satisfaction × tenure	0.001*** (0.001)	0.002*** (0.000)	0.002*** (0.000)
Lagged satisfaction × GDP growth	0.002 (0.002)	0.002 (0.001)	−0.001 (0.002)
Lagged satisfaction × regional unemployment	0.0001 (0.001)	0.0001 (0.001)	−0.001 (0.001)
Lagged satisfaction × job insecurity	0.019*** (0.007)	0.0001 (0.004)	0.004 (0.006)
Lagged satisfaction × age	0.001** (0.000)	0.002*** (0.000)	0.001*** (0.000)
Lagged satisfaction × education	−0.005*** (0.001)	−0.006*** (0.001)	−0.002 (0.001)
Lagged satisfaction × public sector	0.021** (0.009)	0.024*** (0.005)	0.018* (0.010)
Gender: male	0.143*** (0.046)	0.098*** (0.030)	
Age	0.026*** (0.004)	−0.019*** (0.003)	
Age squared/100	−0.086*** (0.006)	−0.022*** (0.004)	−0.029*** (0.008)
Years of job tenure	−0.060*** (0.004)	−0.047*** (0.003)	−0.005 (0.003)
Job tenure squared/100	0.090*** (0.011)	0.070*** (0.006)	0.021** (0.008)
Real GDP growth rate	−0.062 (0.048)	−0.037 (0.029)	0.021 (0.044)
Regional unemployment rate	−0.010 (0.008)	−0.007 (0.005)	−0.009 (0.006)
Subjective job insecurity	0.184*** (0.041)	0.193*** (0.025)	0.140*** (0.043)
Fixed-term contract	0.516*** (0.031)	0.391*** (0.025)	0.266*** (0.045)
Years of education	0.096*** (0.010)	0.085*** (0.007)	
Public sector	−0.397*** (0.079)	−0.319*** (0.050)	−0.162* (0.077)
Constant		0.690*** (0.116)	0.574*** (0.175)
R^2		0.249	0.053
N	36,952	36,952	36,952

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, standard errors clustered on regions in parentheses

Year, sector, and firm size dummies included

Data: GSOEP 1985, 1987, 1989, 1991, 1993, 1994, 1996, 1998, 1999, 2001, 2003, 2005

(a) Dependent variable “cardinalized” as described in Appendix A1

Tab. 4.5: Job change regressions

Model	Pooled probit	Pooled OLS	Fixed-effects linear
Subj. probability of job search	0.215*** (0.066)	0.069*** (0.014)	0.065*** (0.021)
Search × satisfaction	−0.010* (0.006)	−0.004*** (0.001)	−0.005*** (0.001)
Search × male	−0.024 (0.023)	−0.000 (0.002)	−0.001 (0.005)
Search × tenure	0.012*** (0.003)	−0.002*** (0.000)	−0.001*** (0.000)
Search × GDP growth	−0.009 (0.007)	0.004*** (0.001)	0.003*** (0.001)
Search × regional unemployment	−0.002 (0.003)	−0.002*** (0.000)	−0.001 (0.001)
Search × experience	0.003*** (0.001)	0.000 (0.000)	−0.000 (0.000)
Search × education	0.015*** (0.004)	0.002** (0.001)	0.002** (0.001)
Search × public sector	−0.018 (0.022)	−0.020*** (0.003)	−0.018*** (0.004)
Job satisfaction	0.002 (0.017)	0.006*** (0.001)	0.004** (0.002)
Gender: male	0.115* (0.067)	0.004 (0.003)	
Years of job tenure	−0.141*** (0.010)	−0.003*** (0.000)	0.004*** (0.001)
Job tenure squared/100	0.288*** (0.024)	0.013*** (0.001)	0.006* (0.003)
Real GDP growth rate	−0.018 (0.139)	−0.011 (0.009)	−0.033*** (0.011)
Regional unemployment rate	−0.011 (0.007)	0.002** (0.001)	0.003* (0.001)
Years of work experience	0.029*** (0.006)	0.002*** (0.000)	−0.015*** (0.002)
Work experience squared/100	−0.133*** (0.016)	−0.005*** (0.001)	0.004 (0.003)
Years of education	−0.035*** (0.012)	−0.003*** (0.001)	
Public sector	−0.240*** (0.080)	0.018*** (0.003)	0.015* (0.009)
Constant	−1.376*** (0.226)	−0.024 (0.018)	0.065** (0.029)
R^2		0.073	0.052
N	47,175	47,175	47,175

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, standard errors clustered on regions in parentheses

Year, sector, and firm size dummies included

Data: GSOEP 1985, 1987, 1989, 1991, 1993, 1994, 1996, 1998, 1999, 2001, 2003, 2005

4.6 Appendix: Details of the estimation

Equations (4.1)-(4.3) form a recursive system of equations that can be estimated by treating each of the equations separately. The inclusion of fixed effects is not so straightforward in models for binary or more general ordinal dependent variables such as the (ordered) probit and the (ordered) logit model. The fixed-effects probit model leads to inconsistent parameter estimates (see for example Baltagi 2001, p. 206 or Hsiao 2003, p.194), and the fixed-effects logit model can only be estimated on the subsample of individuals that have longitudinal variation in the dependent variable, which leads to small sample sizes and selective samples[10]. To circumvent these problems, I applied linear fixed-effects models to the binary and to the ordinal dependent variables. In the case of multinomial ordered variables with more than two classes (job satisfaction and job search), I rescaled the dependent variable before applying the linear regression model as proposed by van Praag and Ferrer-i-Carbonel (2004). The rescaling makes the coefficients of the linear model comparable with the coefficients of the ordered probit model. Van Praag and Ferrer-i-Carbonel (2004) call this probit-adapted OLS (POLS). The rescaling consists of deriving those Z-values of a standard normal distribution that correspond to the cumulative frequencies of the different categories of the ordinal dependent variable. Suppose an ordinal variable x coded from 1 to 4 has the following distribution: *p(x=1)=0.1, p(x=2)=0.3, p(x=3)=0.5,* and *p(x=4)*=0.1. The cumulated frequencies are then *P(x=1)=0.1, P(x=2)=0.4, P(x=3)=0.9*, and *P(x=4)*=1, and the corresponding Z-values of the standard normal distribution are: $Z_{0.1} = -1.28$, $Z_{0.4} = -.25$, $Z_{0.9} = 1.28$, and $Z_1 = \infty$. For a given value of the original ordinal variable, the value of the 'cardinalized' dependent variable is constructed by considering the expectation of a standard normally distributed variable under the condition that it is in the interval between those two Z-values that correspond to the class of the value of the original variable. In the above example, this means that cardinalized variable x_c takes on the values:

[10]If the job change equation is estimated by a fixed-effects logit model instead of the linear fixed-effects model, the sample size shrinks from 47175 to 7050 and individuals in the restricted sample differ systematically from those in the complete sample. For example, the sample quit rate rises from 0.035 to 0.21 and mean work experience in the sample falls from 21 to 17 years.

$$x_c = \begin{cases} E(Z|Z < -1.28) = \dfrac{-\phi(-1.28)}{\Phi(-1.28)} & \text{if} \quad \text{x} = 1 \\ E(Z| - 1.28 < Z < -0.25) = \dfrac{\phi(-1.28) - \phi(-0.25)}{\Phi(-0.25) - \Phi(-1.28)} & \text{if} \quad \text{x} = 2 \\ E(Z| - 0.25 < Z < 1.28) = \dfrac{\phi(-0.25) - \phi(1.28)}{\Phi(1.28) - \Phi(-0.25)} & \text{if} \quad \text{x} = 3 \\ E(Z|1.28 < Z) = \dfrac{\phi(1.28)}{1 - \Phi(1.28)} & \text{if} \quad \text{x} = 4 \end{cases},$$

where Z is a standard normal random variable, ϕ being the standard normal probability density function, and Φ being the standard normal cumulative density function, which leads to:

$$x_c = \begin{cases} -1.75 & \text{if} \quad \text{x} = 1 \\ -.70 & \text{if} \quad \text{x} = 2 \\ .42 & \text{if} \quad \text{x} = 3 \\ 1.75 & \text{if} \quad \text{x} = 4 \end{cases}$$

In principle, I follow this approach but I replace the Z-values from the standard normal distribution by the cutoff points from the ordered probit regression instead. I prefer this approach because it uses the information of the whole model and not only the frequency distribution of the dependent variable for the re-scaling.

Part II

Methodological tools

Chapter 5

Standard errors of marginal effects in the heteroskedastic probit model [1]

The analysis of the effect of wage rigidity on job mobility in chapter 2 relies on the estimation of heteroskedastic probit models. In such a non-linear regression model coefficients cannot be interpreted as marginal effects. The marginal effect of a regressor is obtained by calculating the derivative of the outcome probability with respect to the regressor. The derivative can be calculated analytically or numerically.

Standard errors of marginal effects also need to be derived to allow inference and hypothesis testing. If the marginal effect is a non-linear transformation of the regression coefficients, the standard error of the marginal effect can only be calculated approximately by methods such as the delta method (see section 5.2). This involves calculating the derivatives of the marginal effect with respect to all coefficients. Again, the derivatives can be computed analytically or numerically.

For the heteroskedastic probit model, the analytical form of the marginal effect is commonly stated (see for example Greene 2003, p. 680), but the derivatives of the marginal effect needed for calculating its standard errors are not. In the statistical software package Stata, the `hetprob` command computes coefficients and standard errors of coefficients of the heteroskedastic probit model. When marginal effects are needed, Stata offers the `mfx` command which numerically computes marginal effects and their standard errors after regression commands. In the case of the heteroskedastic probit

[1] This chapter is available as Discussion Paper No. 320 of the discussion paper series of the Faculty of Economics and Business Administration at Leibniz Universität Hannover.

model and when many regressors are involved, this procedure is somewhat time consuming.[2]

This chapter presents the analytical computation of the standard errors of the marginal effects in a heteroskedastic probit regression and the associated Stata ado-file `mehetprob` that is downloadable for public use. The method presented here was used in the analysis presented in chapter 3 of this thesis.

The chapter is organized as follows. Section 5.1 describes the marginal effect of a regressor in the heteroskedastic probit model. Section 5.2 covers the delta method and section 5.3 applies the method in order to derive the standard errors of the heteroskedastic probit model. Section 5.4 provides information on how to access the Stata ado-file and presents an application which compares the analytical calculation with the numerical one. Section 5.5 concludes.

5.1 The marginal effect in the heteroskedastic probit model

The heteroskedastic probit model extends the simple probit model by introducing heteroskedasticity of the error term of the latent variable. Let the latent variable be

$$y_i^* = x_i'\beta + \epsilon_i, \tag{5.1}$$

where i indexes observations, x is an $s \times 1$ vector of covariates including the regressor 1, β a corresponding coefficient vector and ϵ a normally distributed error term satisfying

$$E[\epsilon_i] = 0, \tag{5.2}$$

$$V[\epsilon_i] = \sigma_i^2 = [exp(z_i'\gamma)]^2, \tag{5.3}$$

and

$$Cov[\epsilon_i, \epsilon_j] = 0, \quad i \neq j, \tag{5.4}$$

[2]This depends very much on the size of the model and the data set and on which release of Stata is used. In Stata 8, the computation of marginal effects with `mfx` after `hetprob` can take hours, while in Stata 9 it has been speeded up to the range of minutes. See section 5.4 for running times of a practical application.

where z is a $t \times 1$ vector of regressors determining the variance of the error term, and γ is the corresponding coefficient vector.

Let the observed binary variable y depend on the latent variable y^* such that

$$y_i = \begin{cases} 1 & \text{if } y_i^* > 0 \\ 0 & \text{if } y_i^* \leq 0, \end{cases} \tag{5.5}$$

then the probability of a success is given by

$$P(Y_i = 1) = P(\epsilon_i > -x_i'\beta) = 1 - \Phi\left(\frac{-x_i'\beta}{exp(z_i'\gamma)}\right) = \Phi\left(\frac{x_i'\beta}{exp(z_i'\gamma)}\right) \tag{5.6}$$

where Φ is the c.d.f of the standard normal distribution.

Unite the x and z regressors in vector $w' = (x', z')$ of length $l = s + t$. For each regressor w_k, $k = 1, \ldots, l$, a marginal effect has to be derived.

Corresponding to the $l \times 1$ vector w define coefficient vectors b and g of the same length l such that

$$b_k = \begin{cases} \beta_j & \text{if } w_k \text{ is the } j\text{th element of } x \\ 0 & \text{otherwise}, \end{cases} \tag{5.7}$$

and

$$g_k = \begin{cases} \gamma_j & \text{if } w_k \text{ is the } j\text{th element of } z \\ 0 & \text{otherwise}. \end{cases} \tag{5.8}$$

The kth element of b contains the β coefficient associated with w_k if w_k is part of the x vector, otherwise it is 0. Similarly, the kth element of g contains the γ coefficient associated with w_k if w_k is part of the z vector, otherwise it is 0.

Suppose a regressor that is part of x and z, then it will appear two times in w, say $w_i = w_j$. Consequently, $b_i = b_j$ and $g_i = g_j$. The marginal effects and standard errors of the marginal effects derived for w_i and w_j will then be the same.

The marginal effect of one regressor w_k is function of all β and γ parameters that may be assembled in a vector $\theta' = (\beta', \gamma')$ of same length $(l = s + t)$ as w.
If w_k is to be treated as a continuous variable, the marginal effect of the outcome probability with respect to this regressor, $g(w_k)$, is found by deriving (5.6) with respect to w_k, which yields

$$g_C(w_k) = \frac{\partial P(Y = 1)}{\partial w_k} = \phi\left(\frac{x'\beta}{exp(z'\gamma)}\right) \frac{b_k - x'\beta \cdot g_k}{exp(z'\gamma)}, \tag{5.9}$$

(see Greene 2003, p.680).

If w_k is element of both, the x and the z vector, then b_k and g_k are the coefficients associated with the regressor w_k in the mean equation (5.1) and the variance equation (5.3) respectively. If w_k is only element of x but not of z, then g_k is zero by definition, i.e. only the first part of (5.9) applies, and if w_k is only element of z but not of x, then b_k is zero by definition, i.e. only the last part of (5.9) applies. If w_k is a dummy variable, the marginal effect of the outcome probability with respect to this regressor, $g(w_k)$, can alternatively, i.e. if the dummy variable is not to be treated as a continuous variable, be calculated as

$$g_D(w_k) = \Phi\left(\frac{x_1'\beta}{exp(z_1'\gamma)}\right) - \Phi\left(\frac{x_0'\beta}{exp(z_0'\gamma)}\right), \tag{5.10}$$

where w_k is set to 1 in x_1 and z_1 and set to 0 in x_0 and z_0 (provided that the regressor is part of the respective vectors).

The marginal effect can be evaluated at different values of the regressors, i.e. a marginal effect for each individual can be calculated. Usually a summary statistic is warranted and thus the marginal effect is evaluated at a specific point, e.g. at means or at the median. Alternatively, a (weighted) average of the individual specific marginal effects can be calculated.

There is an important distinction between the normal probit model and the heteroskedastic probit model. In the normal probit model the marginal effect of a regressor x_k for individual i is given by $\phi(x_i'\beta) \cdot \beta_k$. As $\phi(\cdot)$ is always positive, the marginal effect has the same sign as the regression coefficient for all individuals in the sample. In the heteroskedastic probit model, the sign of the marginal effect depends on $b_k - x'\beta \cdot g_k$ (see equation (5.9)), which can switch sign in the sample for regressors that are part of both x and z and for regressors that are only part of z. Therefore it can be of interest to calculate the individual marginal effects and check for which fraction of the sample the effect is positive or negative.

For the following application of the delta method suppose that one marginal effect for each regressor w_k, $k = 1, \ldots, l$ is calculated at specific values of the regressors (e.g. at means). This leads to a $l \times 1$ vector of estimated marginal effects $\hat{\lambda}$.

5.2 The delta method

The delta method is a popular way to estimate standard errors of non-linear functions of model parameters. While it is straightforward to calculate the variance of a linear function of a random variable, it is not for a nonlinear function. The delta method therefore relies on finding a linear approximation of the function by using a first-order Taylor expansion (see e.g. Davidson/MacKinnon 2004, p.202). In the multivariate case, let $\hat{\lambda} = \mathbf{g}(\hat{\theta})$ be a $l \times 1$ vector of monotonic continuously differentiable functions of the $n \times 1$ coefficient estimator $\hat{\theta}$. Then, for a given estimated covariance matrix of the model parameters, $\hat{V}(\hat{\theta})$, the covariance matrix of $\hat{\lambda}$, can be estimated according to the delta method by

$$\hat{V}(\hat{\lambda}) = \hat{G}\hat{V}(\hat{\theta})\hat{G}', \tag{5.11}$$

where $\hat{\mathbf{G}} \equiv \mathbf{G}(\hat{\theta})$ is the $l \times n$ matrix $\partial\mathbf{g}(\theta)/\partial\theta'$. The ith row of $\mathbf{G}(\hat{\theta})$ is the vector of partial derivatives of the ith function with respect to $\hat{\theta}'$ or, in other words, the typical element in row i and column j of $\mathbf{G}(\hat{\theta})$ is $\partial g_i(\theta)/\partial\theta_j$ (Davidson/MacKinnon 2004, p. 208).

5.3 Applying the delta method to standard errors of marginal effects of the heteroskedastic probit model

In the heteroskedastic probit model as defined above there is a $(l = s + t) \times 1$ vector w of regressors entering the model. For each regressor w_k a marginal effect is derived, which is function of all β and γ parameters that may be assembled in a $1 \times (l = s + t)$ vector $\theta' = (\beta', \gamma')$.[3]

The $l \times 1$ vector of marginal effects is $\hat{\lambda} = \mathbf{g}(\hat{\theta})$ with its kth element being the marginal effect $g(w_k)$ as defined in (5.9) and (5.10).

The element (k, j) of the $l \times l$ matrix $\mathbf{G}(\hat{\theta})$ contains the derivative of $g(w_k)$ with respect to the coefficient θ_j, whereby θ_j may be (i) a β coefficient not associated with

[3]Recall that s is the length of x and β, t is the length of z and γ.

w_k, (ii) a β coefficient associated with w_k, (iii) a γ coefficient not associated with w_k, or (iv) a γ coefficient associated with w_k.[4] For these four cases, and if the regressors are treated as continuous, the derivatives are:

(i) If θ_j is a β coefficient not associated with w_k:

$$\begin{aligned}\partial g_C(w_k)/\partial\theta_j &= -b_k w_j (x'\beta)\frac{\phi\left(\frac{x'\beta}{exp(z'\gamma)}\right)}{[exp(z'\gamma)]^3} \\ &\quad -g_k w_j \frac{\phi\left(\frac{x'\beta}{exp(z'\gamma)}\right)}{exp(z'\gamma)}\left(1-\frac{(x'\beta)^2}{[exp(z'\gamma)]^2}\right) \end{aligned} \tag{5.12}$$

(ii) If θ_j is a β coefficient associated with w_k:

$$\begin{aligned}\partial g_C(w_k)/\partial\theta_j &= \frac{\phi\left(\frac{x'\beta}{exp(z'\gamma)}\right)}{exp(z'\gamma)} - b_k w_j (x'\beta)\frac{\phi\left(\frac{x'\beta}{exp(z'\gamma)}\right)}{[exp(z'\gamma)]^3} \\ &\quad -g_k w_j \frac{\phi\left(\frac{x'\beta}{exp(z'\gamma)}\right)}{exp(z'\gamma)}\left(1-\frac{(x'\beta)^2}{[exp(z'\gamma)]^2}\right) \end{aligned} \tag{5.13}$$

(iii) If θ_j is a γ coefficient not associated with w_k:

$$\begin{aligned}\partial g_C(w_k)/\partial\theta_j &= (b_k - x'\beta\cdot g_k)\,\frac{w_j\cdot\phi\left(\frac{x'\beta}{exp(z'\gamma)}\right)}{exp(z'\gamma)}\cdot \\ &\quad \cdot\left(\frac{(x'\beta)^2}{[exp(z'\gamma)]^2}-1\right) \end{aligned} \tag{5.14}$$

(iv) If θ_j is a γ coefficient associated with w_k:

$$\begin{aligned}\partial g_C(w_k)/\partial\theta_j &= (b_k - x'\beta\cdot g_k)\,\frac{w_j\cdot\phi\left(\frac{x'\beta}{exp(z'\gamma)}\right)}{exp(z'\gamma)}\left(\frac{(x'\beta)^2}{[exp(z'\gamma)]^2}-1\right) \\ &\quad -\frac{\phi\left(\frac{x'\beta}{exp(z'\gamma)}\right)\cdot x'\beta}{exp(z'\gamma)} \end{aligned} \tag{5.15}$$

[4]The distinction whether w_k is part of x, z or both enters through the components of b and g being zero if w_k is not in x or z, respectively.

Hereby, all regressors are evaluated at the same values that have been chosen to evaluate the marginal effect, e.g. at means. Recall that b_k (g_k) is zero by definition if w_k is only element of x (z). In that case, the derivatives simplify accordingly.

If regressor w_k is a dummy variable that is not to be treated as a continuous variables, the derivative of $g_D(w_k)$ in (5.10) is used, which is

(i) If θ_j is a β coefficient:

$$\partial g_D(w_k)/\partial\theta_j = w_{1j} \cdot \frac{\phi\left(\frac{x_1'\beta}{exp(z_1'\gamma)}\right)}{exp(z_1'\gamma)} - w_{0j} \cdot \frac{\phi\left(\frac{x_0'\beta}{exp(z_0'\gamma)}\right)}{exp(z_0'\gamma)} \tag{5.16}$$

(ii) If θ_j is a γ coefficient:

$$\begin{aligned}\partial g_D(w_k)/\partial\theta_j \quad &= \quad \frac{-w_{1j} \cdot (x_1'\beta)\phi\left(\frac{x_1'\beta}{exp(z_1'\gamma)}\right)}{exp(z_1'\gamma)} \\ &\quad + \frac{w_{0j} \cdot (x_0'\beta)\phi\left(\frac{x_0'\beta}{exp(z_0'\gamma)}\right)}{exp(z_0'\gamma)},\end{aligned} \tag{5.17}$$

where w_{0j} and w_{1j} are the jth element of the vectors $w_0' = (x_0', z_0')$ and $w_1' = (x_1', z_1')$, respectively. The vectors x_0, z_0, x_1 and z_1 have been defined in the discussion of equation (5.10).

These derivatives allow to compute $\hat{\mathbf{G}} \equiv \mathbf{G}(\hat{\theta}) = \partial\mathbf{g}(\hat{\theta})/\partial\hat{\theta}'$ and to calculate the standard errors of the marginal effects by using equation (5.11).

5.4 Stata ado-file and application

The computation of marginal effects and their standard errors that has been derived analytically in the preceding section has been programmed as a Stata ado-file called `mehetprob`. This file and the associated help file are available for download at the Statistical Software Components (SSC) archive at the Boston College. The recommended way to download it is by typing `ssc install mehetprob` in the Stata command line. Alternatively, to view a description type `ssc describe mehetprob`.[5]

In the following, an application is presented. A heteroskedastic probit regression is run with data from the German Socio-Economic Panel. An overview of the data set is provided by Haisken-DeNew/Frick (2003). West German private sector workers are sampled. The dependent variable quit1 takes on the value 1 if a worker quits his job in the next period and 0 otherwise. Explanatory variables are the hourly wage (w_h4), the actual working hours (hoursact), sex (male), dummies for increasing firm size categories (fsize2, fsize3, fsize4), a dummy that indicates foreign nationality (foreign), age, age squared (agesq), tenure and the regional unemployment rate (regunemp). All variables enter the main equation (the x vector in terms of the notation used earlier), tenure and the hourly wage also enter the equation for modelling the variance of the error term (the z vector).

The output from the regression is:

```
Heteroskedastic probit model                      Number of obs     =     57294
                                                  Zero outcomes     =     54277
                                                  Nonzero outcomes  =      3017

                                                  Wald chi2(11)     =    829.77
Log likelihood = -10478.78                        Prob > chi2       =    0.0000

------------------------------------------------------------------------------
       quit1 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
quit1        |
        w_h4 |   .0117582   .0022307     5.27   0.000     .0073862    .0161303
    hoursact |   .0023257   .0011014     2.11   0.035      .000167    .0044845
        male |  -.0577722   .0223677    -2.58   0.010     -.101612   -.0139323
      fsize2 |   -.100491   .0245272    -4.10   0.000    -.1485634   -.0524186
      fsize3 |  -.2425828    .029201    -8.31   0.000    -.2998157   -.1853498
      fsize4 |  -.3415201    .032397   -10.54   0.000    -.4050171   -.2780231
     foreign |   -.210218   .0249594    -8.42   0.000    -.2591375   -.1612984
         age |   .0608655   .0074646     8.15   0.000     .0462352    .0754959
       agesq |  -.0010025   .0001049    -9.56   0.000    -.0012081   -.0007969
      tenure |  -.1485081   .0070428   -21.09   0.000    -.1623117   -.1347045
    regunemp |  -.0199462   .0036634    -5.44   0.000    -.0271263   -.0127662
       _cons |  -1.646515   .1288987   -12.77   0.000    -1.899152   -1.393879
-------------+----------------------------------------------------------------
lnsigma2     |
      tenure |    .033426   .0015828    21.12   0.000     .0303239    .0365282
        w_h4 |  -.0083866   .0018145    -4.62   0.000     -.011943   -.0048302
------------------------------------------------------------------------------
Likelihood-ratio test of lnsigma2=0: chi2(2) =   269.38    Prob > chi2 = 0.0000
```

All coefficients are highly significant and have the expected sign, at least for those variables that are only in the main equation, as the sign of their marginal effect on the

[5]Type `help ssc` to get information on the `ssc` command that allows to manage the user written software components from the SSC archive.

propensity to quit must equal the sign of the regression coefficients. For tenure and the hourly wage the sign of the marginal effect is not clear, because they enter the mean and the variance equation and thus the sign can switch depending on the regressor values at which the marginal effect is evaluated. The likelihood-ratio test reported at the bottom of the regression output rejects a model without heteroskedasticity. Below the output from `mfx` and `mehetprob` for the computation of marginal effects and their standard errors is presented.

```
. mfx compute;

Marginal effects after hetprob
      y  = Pr(quit1) (predict)
         =  .02091509
------------------------------------------------------------------------------
variable |      dy/dx    Std. Err.     z    P>|z|  [    95% C.I.   ]      X
---------+--------------------------------------------------------------------
    w_h4 |  -.0003846      .00013   -2.91   0.004  -.000644 -.000126   11.8481
hoursact |   .0000937      .00004    2.10   0.036   6.2e-06  .000181   39.5301
   male*|  -.0023583      .00092   -2.55   0.011  -.004168 -.000549    .63504
  fsize2*|  -.0039146      .00094   -4.18   0.000  -.005752 -.002077   .289297
  fsize3*|   -.008871      .00101   -8.75   0.000  -.010859 -.006883   .244615
  fsize4*|   -.011988      .00107  -11.25   0.000  -.014076   -.0099   .237774
 foreign*|  -.0078578      .00092   -8.51   0.000  -.009667 -.006049   .271756
     age |   .0024525      .00028    8.63   0.000   .001895   .00301   37.9823
   agesq |  -.0000404      .00000  -10.21   0.000  -.000048 -.000033   1572.87
  tenure |  -.0025629      .00011  -22.95   0.000  -.002782 -.002344   9.60174
regunemp |  -.0008037      .00015   -5.38   0.000  -.001096 -.000511   8.54533
------------------------------------------------------------------------------
(*) dy/dx is for discrete change of dummy variable from 0 to 1


. mehetprob;
(obs=57294)
(obs=57294)
P(Y=1) in sample:                  .05265822
P(Y=1) mean of model prediction:   .05267644
P(Y=1) predicted at means:         .02091509

dP/dX - Marginal effect at means after heteroskedastic probit estimation:

    Variable |       dP/dX        s.e.           z       P
-------------+--------------------------------------------
        w_h4 |   -.0003846    .0001321       -2.91   0.004
    hoursact |    .0000937    .0000446        2.10   0.036
       male* |   -.0023583    .0009232       -2.55   0.011
     fsize2* |   -.0039146    .0009374       -4.18   0.000
     fsize3* |    -.008871    .0010143       -8.75   0.000
     fsize4* |    -.011988    .0010654      -11.25   0.000
    foreign* |   -.0078578     .000923       -8.51   0.000
         age |    .0024525    .0002843        8.63   0.000
       agesq |   -.0000404    3.96e-06      -10.21   0.000
      tenure |   -.0025629    .0001117      -22.95   0.000
    regunemp |   -.0008037    .0001493       -5.38   0.000
----------------------------------------------------------
(*) dP/dx is for discrete change of dummy variable from 0 to 1
```

The results are exactly the same. All marginal effects at means are highly significant. Wage and tenure have negative marginal effect at means. As would be expected, the propensity to quit decreases with rising hourly wages and with longer tenure.

Calculating the marginal effects at means with the `mfx` command takes a running time of 3 hours and 25 minutes in Stata 8. In Stata 9, where the `mfx` command has been speeded up, it takes 1 minute and 24 seconds. The calculation with the `mehetprob` routine takes 3 seconds. Table 5.1 compares the running time of the calculation of the marginal effects at means between the numerical computation by `mfx` in Stata 8 and Stata 9 and the analytical computation by the `mehetprob` routine for two different models.

Tab. 5.1: Comparison of computing time in different models

	Small model	Large model
Size		
No. Regressors	11	44
No. Observations	57294	87487
Running Time (hh:mm:ss)$^{a)}$		
mfx Stata 8	03:25:00	> 39:00:00
mfx Stata 9	00:01:24	00:10:45
mehetprob	00:00:03	00:00:08

a) Hardware specification: CPU 1,92 Ghz, 200 MB RAM allocated to Stata

Model 1 is the one presented above with 11 regressors and 57,294 observations. In model 2 more regressors, e.g. time and sector dummies, are added and the sample is extended to East German and public sector workers. This leads to 44 regressors and 87,487 observations (regression results not reported here). While `mehetprob` took 8 seconds, `mfx` in Stata 9 took about 10 minutes and `mfx` in Stata 8 more than 39 hours.

Although the `mfx` command is considerably faster in Stata 9 as compared to Stata 8, the `mehetprob` routine still saves running time. It seems that the larger the model and the number of observations, the greater is the factor by which `mehetprob` is faster. For example, comparing `mfx` of Stata 9 with `mehetprob` shows that `mehetprob` is faster by a factor of 28 (3 seconds versus 1 minute 24 seconds) in model 1 and by a factor of 81 in model 2 (8 seconds versus 10 minutes 45 seconds).

5.5 Conclusion

This chapter has derived an analytical form of the standard errors of marginal effects in a heteroskedastic probit model. The computation has been implemented as a Stata ado-file which can be downloaded from the internet. This allows to compute marginal effects at means and their standard errors in a heteroskedastic probit model faster than by numerical calculation which is implemented in the `mfx` routine currently available in Stata for that purposes. For users of Stata 8 the routine can save hours of computation time, for users of Stata 9 it saves minutes, as the `mfx` command has been speeded up considerably in the Stata 9 release.

Chapter 6

The stata module felsdvreg to fit a linear model with two high-dimensional fixed effects[1]

Fixed-effects models are popular in applied econometric work because they allow to take into account time-constant unobserved heterogeneity that may be correlated with observed characteristics. In recent years large-scale linked employer-employee data, linked student-teacher data, and other types of linked data have become available. Such data allow to include at least two fixed effects into the analysis, for example person and firm effects or student and teacher effects. As the data sets involved usually include high numbers of observations, these fixed effects are often high-dimensional, i.e. there are a high number of panel units (workers, firms, teachers, students). Applications of such models can be found in the fields of labor economics and educational economics. For example, Abowd, Kramarz and Margolis 1999, Abowd, Creecy and Kramarz 2002 and Andrews et al. 2006a estimate wage equations including person and firm effects, and Harris and Sass (2007) estimate a model of student achievement including student, teacher and school effects. The analysis presented in chapter 3 of this thesis is another example of such an application.

Due to the size of the data sets involved, the researcher often encounters computer restrictions in terms of computer memory space and computing time. This chapter, and the companion Stata module `felsdvreg`, deal with the first restriction, the limitation

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of computer memory. I present a memory-saving way to estimate a fixed-effects model with two high-dimensional fixed effects. It relies on the idea that a typical dummy variable matrix of fixed effects, such as firm or teacher effects, is a sparse matrix. Sparse matrices can be stored efficiently in compressed form. The method was used for the analysis presented in chapter 3 and implemented in a ready-to-use Stata ado file. This program takes care of the identification problem, computes the estimates and provides useful summary statistics.

The chapter is organized as follows. Section 6.1 presents the model. Section 6.2 points out the computer restrictions and describes how the estimation can be organized in a memory-efficient way. Section 6.3 summarizes the steps of the estimation. Section 6.4 presents the implementation of the method in a Stata ado-file and comments the output of the program. Section 6.5 concludes.

Throughout the chapter I refer to linked employer-employee data sets calling the two effects to be estimated person and firm effects. I refer to stayers as those individuals that are observed in only one firm and to movers as those who are observed in several firms. Despite the terminology used the method can be directly transfered to other types of matched data sets.

6.1 The linear fixed-effects model with two high-dimensional fixed effects

Consider the following model which can be applied to linked employer-employee panel data including data on individuals and firms. The model is

$$\tilde{y} = \tilde{X}\beta + \tilde{D}\theta + \tilde{F}\psi + \tilde{\epsilon}, \tag{6.1}$$

where $\tilde{X}(N^* \times K)$ is the design matrix of time varying characteristics; $\tilde{D}(N^* \times N)$ is the design matrix for the person effects; and $\tilde{F}(N^* \times J)$ is the design matrix for the firm effects. N^* is the number of person-years in the dataset, J is the number of firms, N is the number of persons and K is the number of time varying regressors. The $\tilde{}$ reflects that (6.1) is the untransformed model.

Further effects, such as fixed time effects, are subsumed in $\tilde{X}$ together with the other time-varying regressors. In a student-teacher context, further effects subsumed in $\tilde{X}$ might be school effects. But any fixed effects remaining in $\tilde{X}$ should not be high-dimensional (relative to the computer memory available), because only the effects in $\tilde{D}$ and $\tilde{F}$ are in the following treated as high-dimensional.

A common way to estimate such a model is to include one of the effects (here the firm effect) as dummy variables, and to sweep out the other effect (here the person effect) by the within transformation or fixed effects transformation. This transformation consists in subtracting the group mean (here the person mean) for all observations. The D matrix becomes the null matrix, the person effects are eliminated from the model. Write the transformed model as:

$$y = X\beta + F\psi + \epsilon, \tag{6.2}$$

where ϵ is an error term satisfying the assumptions of the classical linear regression model. Abowd, Kramarz and Margolis (1999) note that this procedure is algebraically equivalent to the full dummy variable model. Andrews et al. (2006a) call this procedure the "FEiLSDVj" method in order to emphasize that the model combines the classical fixed effects (FE) model and the least squares dummy variable model (LSDV), as one effect is eliminated by the fixed effects transformation and the other included as dummy variables. As pointed out by Greene (2003, p. 293), this procedure is adequate for balanced and unbalanced panels alike[2].

The system of normal equations is:

$$A \begin{pmatrix} \beta \\ \psi \end{pmatrix} = B \tag{6.3}$$

with

$$A = \begin{pmatrix} X'X & X'F \\ F'X & F'F \end{pmatrix} \text{ and} \tag{6.4}$$

$$B = \begin{pmatrix} X'y \\ F'y \end{pmatrix} \tag{6.5}$$

Solving this system of equations delivers the coefficient estimates.

[2]For a more general treatment of the matrix algebra involved in representing multiple-way error components models with unbalanced data structures see Davis (2001).

6.2 Creating the moment matrices in a memory-efficient way

In big data sets the design matrix (X, F) can be too large to fit the memory, as most software packages such as Stata require the design matrix to be stored in memory. To illustrate the memory requirement with the explicit creation of all dummy variables consider the following example: A data set contains $N^* = 2,000,000$ observations, $N = 100,000$ persons, $J = 20,000$ firms and $K = 50$ further right-hand side regressors. Assume that one cell of the data matrix consumes 8 bytes (which is the case when working in high-precision mode). The creation of the time-demeaned firm dummies implies storing the design matrix (X, F) in the computer memory. The size of this matrix is $N^* \cdot (K + J) \cdot 8$ bytes $= 320.8$ gigabytes. This is far more than the computer memory available at present to most researchers. It therefore seems that the estimation of person and firm effects using the "FEiLSDVj" method with several millions of observations and several thousands of firms would be impossible with restricted memory resources.

However, note that while the design matrix (X, F) is of dimension $(N^* \times (K + J))$, the cross-product matrices A and B given in (6.4) and (6.5) are of dimension $((K+J) \times (K + J))$ and $((K + J) \times 1)$ only. They require much less storage space. In the above example, the memory requirement for $A = (X, F)'(X, F)$ is only $(K+J)^2 \cdot 8$ bytes $= 3.21$ gigabytes, which is considerably smaller[3].

In fact, A and B can be computed without explicitly creating the full design matrix (X, F). A solution for that problem lies in the fact that each element of A and B is a cross product sum of no more than two regressors. This implies that for computing one element of A or B, only two regressors need to be stored in memory. While the X-part of the design matrix is provided as a dataset, the F-part of the cross-product matrix can be created during the estimation process without actually generating the F-part of the design matrix, i.e. the dummy variables. The information needed for that purpose is condensed in the group identifiers. In other words, the group identifiers provide a compressed storage format of the sparse dummy variable matrices. The following decomposition is based on the fact that the F matrix is a sparse matrix, i.e. large parts

[3] The cross product matrix $B = (X, F)'y$ is negligibly small compared to the matrix A.

of it are null sub-matrices which deliver no contribution to A or B. Therefore, in the process of the formation of A and B, only certain parts of the F matrix need to be created and time and memory can be saved.

Let the persons in the dataset be indexed by i ($i = 1 \dots N$) and the time periods for each individual be indexed by t ($t = 1 \dots T_i$). T_i is the number of time periods that individual i is observed. The total number of observations is then $N^* = \sum_i T_i$. The vector y and the design matrices X and F in (6.2) have row dimension N^* and rows are indexed by the index it. The columns of X are indexed k ($k = 1, \dots K$) and the columns of F are indexed j ($j = 1 \dots J$).

The memory-saving way to create A and B starts from the idea that these matrices can be decomposed by observations or subsets of observations[4]. For example, A (B) can be represented as a sum of matrices A_i (B_i) for each individual:

$$A = \sum_i A_i = \sum_i \begin{pmatrix} X_i'X_i & X_i'F_i \\ F_i'X_i & F_i'F_i \end{pmatrix} \text{ and} \tag{6.6}$$

$$B = \sum_i B_i = \sum_i \begin{pmatrix} X_i'y_i \\ F_i'y_i \end{pmatrix}, \tag{6.7}$$

where X_i is $(T_i \times K)$, F_i is $(T_i \times J)$ and y_i is $(T_i \times 1)$. The matrices involve only those observations that are associated with individual i. For the current purpose it makes sense to do the individual-wise decomposition only for those parts of the matrices, where the F matrix is involved, i.e.:

$$A = \begin{pmatrix} X'X & 0 \\ 0 & 0 \end{pmatrix} + \sum_i \begin{pmatrix} 0 & X_i'F_i \\ F_i'X_i & F_i'F_i \end{pmatrix} \text{ and} \tag{6.8}$$

$$B = \begin{pmatrix} X'y \\ 0 \end{pmatrix} + \sum_i \begin{pmatrix} 0 \\ F_i'y_i \end{pmatrix}. \tag{6.9}$$

The decomposition continues with the idea that the F matrix has a different structure for stayers and for movers. In this context movers are defined as workers who change employer at least once during the whole observation period and stayers are those workers who never change employer.

[4] The possibility of an observation-wise computation of a cross-product matrix is usually presented in econometrics textbooks by two alternative ways of writing the OLS estimator. For example, in Wooldridge (2002, p. 53) it is stated that $\mathbf{X}'\mathbf{X} = \sum_i \mathbf{x}_i'\mathbf{x}_i$, where $\mathbf{x}_i$ are the rows of $\mathbf{X}$.

Recall that the model is a transformed model. Group means by person have been subtracted (time-demeaning / within-transformation). As stayers never change firms, the time-demeaned firm dummies are all zero. The F matrix for stayers is the null matrix. Therefore we get:

$$A = \begin{pmatrix} X'X & 0 \\ 0 & 0 \end{pmatrix} + \sum_{i \,\in\, \text{Movers}} \begin{pmatrix} 0 & X_i'F_i \\ F_i'X_i & F_i'F_i \end{pmatrix} \text{ and} \tag{6.10}$$

$$B = \begin{pmatrix} X'y \\ 0 \end{pmatrix} + \sum_{i \,\in\, \text{Movers}} \begin{pmatrix} 0 \\ F_i'y_i \end{pmatrix}. \tag{6.11}$$

(6.10) and (6.11) are important simplifications of (6.8) and (6.9). As the F matrix is the null matrix in the sub sample of stayers, the cross product sub matrices $X'F$, $F'F$ and $F'y$ only need to be computed for movers[5]. As these matrices can be computed individual by individual, the F matrix does not need to exist completely at any point of time. For example, it suffices to create the matrix F_i for one individual and to compute $X_i'F_i$, $F_i'F_i$ and $F_i'y_i$. F_i is of dimension $(T_i \times J)$ and therefore should fit into the memory. However, by analyzing the structure of F_i more precisely, the matrix can be reduced further and more memory space can be saved.

Look at F_{i^*} for a worker i^* who is observed at $T_{i^*} = 3$ different points in time and changes the firm once. The non time-demeaned matrix $\tilde{F}_{i^*}$ is:

$$\tilde{F}_{i^*} = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & \dots & 0 \\ 1 & 0 & 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & 1 & 0 & \dots & 0 \end{pmatrix} \tag{6.12}$$

Worker i^* is employed during two time periods in firm 1 and during the third time period in firm 4. He is never employed in any other firm, which means that to the right the individual F matrix is filled up with zeros. The corresponding time-demeaned design matrix of the firm effects for individual i^* is:

$$F_{i^*} = \begin{pmatrix} 1/3 & 0 & 0 & -1/3 & 0 & \dots & 0 \\ 1/3 & 0 & 0 & -1/3 & 0 & \dots & 0 \\ -2/3 & 0 & 0 & 2/3 & 0 & \dots & 0 \end{pmatrix} \tag{6.13}$$

Note that for each worker, only very few columns of F_{i^*} will be different from null vectors, because a given worker is employed in very few firms relative to the total set

[5]The matrix $F'X$ is the transpose of $X'F$ an therefore in what follows it is not discussed separately.

of firms. Consequently, many elements of the cross product matrices $X_i'F_i$, $F_i'F_i$ and $F_i'y_i$ are equal to zero. In the appendix (section 6.6), $(X_{i^*}'F_{i^*})$, $(F_{i^*}'F_{i^*})$ and $(F_{i^*}'y_{i^*})$ are computed for the above example. In $(F_{i^*}'F_{i^*})$ the only non-zero elements are those where both row and column indices refer to a firm where worker i was employed at some moment of time. In $(X_{i^*}'F_{i^*})$ only the columns that are indexed with reference to a firm where worker i was employed are non-zero. In $(F_{i^*}'y_{i^*})$ only the rows that are indexed with reference to a firm where worker i was employed are non-zero.

A typical worker is usually employed in very few firms and thus contributes to only very few elements of the cross product matrices. F_i is a sparse matrix, and so are $(X_{i^*}'F_{i^*})$, $(F_{i^*}'F_{i^*})$ and $(F_{i^*}'y_{i^*})$. One can write F_i more compactly by leaving out the zero columns. Call this reduced matrix F_i^S. This is a $T_i \times s$ matrix, where s is the number of firms in which individual i was employed. In the above example, F_i^S would be a (3×2) matrix which reads:

$$F_{i^*}^S = \begin{pmatrix} 1/3 & -1/3 \\ 1/3 & -1/3 \\ -2/3 & 2/3 \end{pmatrix} \tag{6.14}$$

Instead of computing $(X_i'F_i)$, $(F_i'F_i)$ and $(F_i'y_i)$ one can compute $(X_i'F_i^S)$, $(F_i^{S\prime}F_i^S)$ and $(F_i^{S\prime}y_i)$, which saves memory and time. However, one needs the information to which firm the columns of F_i^S refer, because once the cross products are computed, the results need to be added to the correct elements of the A and the B matrix, which is not a problem because this information is stored in the group identifiers. The next section summarizes the algorithm for the fixed effects estimation of the linear three-way error component model in a memory-saving way.

6.3 The algorithm to compute the least squares solution

The memory-saving way to compute the matrices A and B of the normal equations uses the information in which firm a given worker is employed. This allows to compute only those elements of A and B that the worker contributes to. The zero elements of the sparse matrices involved are dropped from the computations.

The steps are the following:

1. Create null matrices A of dimension $((K+J) \times (K+J))$ and B of dimension $((K+J) \times 1)$.

2. Compute $X'X$ and $X'y$ on the combined sample of movers and stayers. Fill in these cross products at the appropriate sub matrices of A and B as shown in (6.8) and (6.9).

3. For each mover $i (i \in \text{ Mover})$ create the time-demeaned matrix F_i but leave out columns that are zero, call this reduced matrix F_i^S. This is a $T_i \times s$ matrix, where s is the number of firms in which individual i was employed. Now,

   a. form $F_i^{S\prime} F_i^S$ and update the A matrix by adding the resulting cross-products to the appropriate elements of A,

   b. form $X_i' F_i^S$ as well as its transpose $(X_i' F_i^S)' = F_i^{S\prime} X_i$ and update the A matrix by adding the resulting cross-products to the appropriate elements of A,

   c. form $F_i^{S\prime} y$ and update the B matrix by adding the resulting cross-products to the appropriate elements of of A.

4. Once A and B are completed, solve for the coefficient vector (β, ψ).

6.4 Implementation in Stata

The method is implemented in Stata in the ado-file `felsdvreg`, the core of which is programmed in Mata. Using Mata in the context of large data sets is an advantage. First, provided that there is enough computer memory, Mata can handle matrices of a dimension of up to 2 billion × 2 billion compared to only 11,000 × 11,000 in the Stata environment (Stata SE). Second, Mata provides computer routines with high numerical precision which is more important in large data sets than in small data sets[6].

[6]In addition to using high-precision routines, cross-checking the results obtained with those obtained in similar but smaller data sets is another way to test whether the size of the data set poses problems of numerical precision. Helpful comments about that topic can be found under the thread ”data set larger than RAM” on the Statalist discussion board http://www.stata.com/statalist/archive/.

Other ways to handle the estimation problem are the approximate procedures as well as two-step and iterative solutions solutions to the exact problem presented in Abowd, Kramarz and Margolis (1999), Abowd, Creecy and Kramarz (2002), Andrews et al. (2006a) and Grütter (2006)[7]. If the sole aim is to control for unobserved heterogeneity and not to compute the person and firm effects explicitly, the ”spell fixed effects” method proposed in Andrews et al. (2006a) is a good alternative to the ”FEiLSDVj” method[8].

In the following, a small simulated linked employer-employee data set is used in order to illustrate the Stata implementation of the estimation method presented in the previous sections. The data set used for the illustration has 100 observations. It comprises 20 workers, for which the dummy variables $p1 \dots p20$ have been created, and 15 firms, for which the dummy variables $f1 \dots f15$ have been created. The dependent variable is called y, the two independent time-varying regressors are called $x1$ and $x2$. The pattern of worker mobility between firms is important because it determines whether person and firm effects can be identified. The firms with movers can be divided into groups within which there is worker mobility, but between which there is no mobility. The table shows to which group the firms with movers belong[9]:

Group	Firms
1	3,4,5
2	6,7,8,9
3	10,11,12
4	13,14,15

Within each such group, one effect is not identified and serves as the reference. If

[7]The classical minimum distance estimator proposed by Andrews et al. (2006a) delivers the same coefficient estimates as the ”FEiLSDVj” method, but it delivers different standard errors, because it is based on separate estimations for movers and stayers, and the error term variance of both estimations is not constrained to be equal.

[8]An alternative Stata module to compute a model with two high-dimensional fixed effects is **a2reg** based on Abowd, Creecy and Kramarz (2002) and available at http://vrdc.ciser.cornell.edu/guides/cg2/html/index.html. This module solves for the coefficient estimates using a solver algorithm suitable for sparse matrices. More generally, all mathematics or statistics packages that include sparse matrix functions could be used as alternatives to the method described here.

[9]An algorithm to determine the groups is derived in Abowd et al. (2002).

the firm with the smallest firm ID is chosen as the reference firm in each group, the effects of firms 3, 6, 10 and 13 are not identified. Furthermore, the effects of firms without movers (firms 1 and 2) are not identified because they can be thought of as forming single groups with only one firm per group.

A common way to estimate a model with person and firm fixed effects is to include the firm effects as dummies and to eliminate the person affects by the within transformation ("FEiLSDVj" method). Knowing that the effects of firms 1, 2, 3, 6, 10 and 13 are not identified in the given example, this can be implemented as follows:

```
. xtreg y x1 x2  f4-f5 f7-f9 f11-f12 f14-f15, fe i(i)

Fixed-effects (within) regression               Number of obs      =       100
Group variable (i): i                           Number of groups   =        20

R-sq:  within  = 0.6518                         Obs per group: min =         1
       between = 0.0015                                        avg =       5.0
       overall = 0.0913                                        max =         9

                                                F(11,69)           =     11.74
corr(u_i, Xb)  = -0.5330                        Prob > F           =    0.0000

------------------------------------------------------------------------------
           y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          x1 |   1.029258   .2151235     4.78   0.000     .6000987    1.458418
          x2 |   -.709482   .2094198    -3.39   0.001    -1.127263   -.2917009
          f4 |    13.2617   3.258081     4.07   0.000     6.762004    19.76139
          f5 |   13.95499   2.818964     4.95   0.000     8.331314    19.57867
          f7 |   8.559977   3.882525     2.20   0.031     .8145504     16.3054
          f8 |   5.433107   3.908214     1.39   0.169    -2.363566    13.22978
          f9 |   11.44951   4.792492     2.39   0.020     1.888749    21.01027
         f11 |   16.76837   3.245567     5.17   0.000     10.29364     23.2431
         f12 |   10.01551   3.407205     2.94   0.004     3.218319     16.8127
         f14 |  -10.19694   3.074528    -3.32   0.001    -16.33046   -4.063427
         f15 |   2.526721   3.844219     0.66   0.513    -5.142287    10.19573
       _cons |  -6.044057    1.03021    -5.87   0.000     -8.09927   -3.988844
-------------+----------------------------------------------------------------
     sigma_u |  10.169633
     sigma_e |  5.4861156
         rho |  .77458273   (fraction of variance due to u_i)
------------------------------------------------------------------------------
F test that all u_i=0:     F(19, 69) =     8.64              Prob > F = 0.0000
```

The person effects can be looked at by:

```
. predict peffxt, u
. table i, c(m peffxt)
------------------------
        i | mean(peffxt)
```

```
----------+------------
        1 |    -9.345165
        2 |    -3.751444
        3 |     12.98728
        4 |    -4.665943
        5 |    -3.879235
        6 |     1.137969
        7 |    -.4461367
        8 |     .4524156
        9 |    -16.23423
       10 |    -12.18615
       11 |    -.4041495
       12 |    -3.953967
       13 |    -11.94854
       14 |    -4.272363
       15 |     1.732473
       16 |    -11.58673
       17 |    -13.57038
       18 |     21.66491
       19 |     14.42718
       20 |      11.0613
-----------------------
```

As described in the previous section, the explicit creation of all firm dummies combined with the use of `xtreg` (let alone the creation of all person and firm dummies with the use of `reg`) can require more computer memory than is available. In the case when there is a large number of firms it can therefore be necessary to apply a memory-saving way to the solution of the "FEiLSDVj" estimator. I have programmed the algorithm presented in the preceding section as a Stata ado-file called `felsdvreg`. This routine can be applied to the present data set as follows:

```
felsdvreg y x1 x2, i(i) j(j) f(feffhat) p(peffhat) m(mover) g(group)
 xb(xb) r(res) mnum(mnum) pobs(pobs)
```

The options are the following: The option **i()** is used to pass the variable name of the person ID, the option **j()** does the same for the firm ID. The options **p()** and **f()** define names of new variables to be created in order to store the person and firm effects after estimation. So do the options **xb()** and **res()** to store the linear combinations $x'\hat{\beta}$ and the residual $\hat{\epsilon}$. The remaining options define names of new variables that store a dummy variable indicating a person who is a mover, **m()**, a group variable indicating the groups of firms connected through mobility, **g()**, a variable containing the number of movers per firm, **mnum()**, and a variable indicating the number of observations per persons, **pobs()**. The output reads:

```
. felsdvreg y x1 x2, i(i) j(j) f(feffhat) p(peffhat) m(mover) g(group) xb(xb) r(res)
mnum(mnum) pobs(pobs)
Memory requirement for moment matrices in GB:
  2.17600e-06

Computing generalized inverse, dimension: 11
  Start:  6 Mar 2008 18:06:02
  End:    6 Mar 2008 18:06:02

N=100
------------------------------------------------------------------------------
             |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          x1 |   1.029258   .2151235     4.78   0.000     .6000987    1.458418
          x2 |  -.7094819   .2094198    -3.39   0.001    -1.127263   -.2917009
------------------------------------------------------------------------------

F-test that person and firm effects are equal to zero: F(28,69)=9.81 Prob > F = 0
F-test that person effects are equal to zero:          F(19,69)=8.64 Prob > F = 0
F-test that firm effects are equal to zero:            F(9,69)=9.97 Prob > F = 0
```

In big data sets, the crucial steps of the estimation concerns the question whether the moment matrices fit into the memory, and how much computing time is required when solving for the coefficients (computing the inverse). Therefore, the above default output contains information on these points. The person and firm effects can be displayed as follows:

```
. table j, c(m feffhat)
-------------------------
        j | mean(feffhat)
----------+--------------
        1 |             0
        2 |             0
        3 |             0
        4 |       13.2617
        5 |      13.95499
        6 |             0
        7 |      8.559977
        8 |      5.433106
        9 |      11.44951
       10 |             0
       11 |      16.76837
       12 |      10.01551
       13 |             0
       14 |     -10.19694
       15 |      2.526721
-------------------------

. table i, c(m peffhat)
-------------------------
```

```
         i | mean(peffhat)
----------+--------------
        1 |     -15.38922
        2 |     -9.795502
        3 |      6.943222
        4 |        -10.71
        5 |     -9.923292
        6 |     -4.906089
        7 |     -6.490194
        8 |     -5.591642
        9 |     -22.27829
       10 |     -18.23021
       11 |     -6.448206
       12 |     -9.998024
       13 |     -17.99259
       14 |     -10.31642
       15 |     -4.311584
       16 |     -17.63079
       17 |     -19.61444
       18 |      15.62085
       19 |      8.383124
       20 |      5.017239
-------------------------
```

The firm effect of the firm without movers and of the reference firm in each group are set to zero. The firm effects are exactly the same as in the `xtreg` estimation (p.102). The person effects differ from the effects of the `xtreg` regression only by the constant -6.044057 of the `xtreg` model, because `felsdvreg` does not by default normalize the sum of the person effects to zero[10].

Using the option **noisily** allows to generate additional output. This option will generate the following additional tables to analyze the structure of the data set:

```
Unique worker-firm combinations: 41

Number of firms workers are employed in:

  Number of |
      firms |      Freq.     Percent        Cum.
------------+-----------------------------------
          1 |          7       35.00       35.00
          2 |          7       35.00       70.00
          3 |          4       20.00       90.00
          4 |          2       10.00      100.00
------------+-----------------------------------
      Total |         20      100.00
```

[10]If the option `cons` is chosen in `felsdvreg`, it does normalize the sum of the person effects to zero and displays a regression constant.

Number of movers (0=Stayer, 1=Mover):

Mover	Freq.	Percent	Cum.
0	7	35.00	35.00
1	13	65.00	100.00
Total	20	100.00	

Number of observations per person:

Obs. per person	Freq.	Percent	Cum.
1	3	15.00	15.00
2	3	15.00	30.00
4	3	15.00	45.00
5	1	5.00	50.00
6	4	20.00	70.00
7	1	5.00	75.00
8	2	10.00	85.00
9	3	15.00	100.00
Total	20	100.00	

Number of movers per firm:

Movers per firm	Freq.	Percent	Cum.
0	2	13.33	13.33
1- 5	7	46.67	60.00
6- 10	5	33.33	93.33
11- 20	1	6.67	100.00
Total	15	100.00	

The first table summarizes in how many firms the workers are employed. The seven workers employed in only one firm are stayers. Out of the remaining 13 workers, 7 are observed in two firms, 4 in three firms and 2 in four firms. The second table is a summary of the first and gives the total number of stayers and movers. The third table indicates the numbers of observations per person. For example, 3 workers are observed only at one point in time, 3 workers are observed 9 times, etc. The fourth table shows the distribution of the number of movers per firm. The purpose of this table is to get an impression of the quality of the estimation of the firm effects. The estimation of the firm effects is better the more movers there are and one might think of the firm effects that are identified by few movers as effects that are poorly estimated. In this example data set two firms have no movers and all 15 firms have less than 20 movers.

The 15 firms can be divided into groups within which there is worker mobility, but between which there is no mobility. As noted above, within each such group, one firm effect is not identified, i.e. one firm effect has to be taken as the reference, and all other firm effects are expressed as differences from the reference. The `felsdvreg` program goes on by defining these groups[11]:

```
Groups of firms connected by worker mobility:

             Person-years       Persons          Movers         Firms

----------------------------------------------------------------------
    group |   N(__000000)    N(__000009)  sum(__00000D)    N(__000008)
----------+-----------------------------------------------------------
        0 |           10              5              0              2
        1 |           26              5              3              3
        2 |           15              2              2              4
        3 |           24              5              5              3
        4 |           25              3              3              3
          |
    Total |          100             20             13             15
----------------------------------------------------------------------

Note: Group 0 in the table regroups firms without movers.

No firm effect in group 0 is identified.
15-2-4 = 9 firm effects are identified.
(number of firms - number of firms without movers - number of groups excl. group 0)
```

The two firms without movers are gathered in group 0. The remaining firms of the sample are divided into 4 groups. The table shows the number of person-years, persons, movers and firms in each of the groups. As indicated, only 9 of the 15 firm effects are identified because 2 firms have no movers and their firm effects cannot be identified, and 4 more firm effects are not identified because they serve as reference in their groups.

The option **noisily** finally generates also the following output:

```
If the covariances are positive, the following may indicate the importance in explaining
the variance of y:

Cov(y, xb) / Var(y):                                .10029458
Cov(y, peffhat) / Var(y):                           .56511312
Cov(y, feffhat) / Var(y):                           .15341486
Cov(y, res) / Var(y):                               .18117743
```

[11]The grouping algorithm incorporated in `felsdvreg` draws on -a2group-, which is a Stata port by Amine Ouazad of the original FORTRAN code written by Robert Creecy and Lars Vilhuber.

This variance decomposition gives an indication of how strongly the four components (i) observed time-varying characteristics, (ii) person effects, (iii) firm effects and (iv) the residual contribute to explaining the variance of the dependent variable. The shares sum to 1, however, the covariances indicated can become negative and then it becomes difficult to interpret the numbers as shares.

After the estimation, the researcher may be interested in correlating the person and firm effects with each other or with other regressors. However, it should be kept in mind that what is actually identified are relative person and firm effects within each group, and that person and firm effects of different groups can only be compared if one is willing to take certain assumptions. This can be illustrated by computing the correlation of person and firm effects over all groups with different normalizations. The first command correlates the person and firm effects over all groups, the second command correlates only the effects of group 1:

```
. corr  feffhat peffhat
(obs=100)

             |  feffhat  peffhat
-------------+------------------
     feffhat |   1.0000
     peffhat |  -0.5645   1.0000

. corr  feffhat peffhat if group==1
(obs=26)

             |  feffhat  peffhat
-------------+------------------
     feffhat |   1.0000
     peffhat |  -0.2006   1.0000
```

Now the firm and person effects are normalized so that they sum to zero within each group by subtracting the average group firm effect and the average group person effect. A new variable `gmean` captures the sum of the mean firm and the mean person effect of each group. After this normalization, the person and firm effects are deviations from the group means. After this, the correlation over all groups and the correlation using only the effects of group 1 are again computed:

```
. by group: egen pmean=mean(peffhat)
. by group: egen fmean=mean(feffhat)
```

```
. gen peffnorm=peffhat-pmean
. gen feffnorm=feffhat-fmean
. gen gmean=pmean+fmean

. table group, c(m gmean)
-----------------------
    group | mean(gmean)
----------+------------
        0 |   -7.385707
        1 |   -1.236314
        2 |   -2.610044
        3 |   -7.291342
        4 |    4.825048
-----------------------

. corr  feffnorm peffnorm
(obs=100)
             | feffnorm peffnorm
-------------+------------------
    feffnorm |   1.0000
    peffnorm |   0.0227   1.0000


. corr  feffnorm peffnorm if group==1
(obs=26)
             | feffnorm peffnorm
-------------+------------------
    feffnorm |   1.0000
    peffnorm |  -0.2006   1.0000
```

The normalization has changed the result from the correlation over all groups[12]. It is now 0.0227 whereas before it was -0.5645. The result of the correlation within the group of -0.2006 is unchanged. One could argue that the normalization of person and firm effects to an equal group mean makes comparison across groups more appropriate and therefore the correlation over all groups after normalization is appropriate whereas the one before normalization was not. However, it seems difficult to argue that a deviation of +1 from a group mean of -7.29 of group 3 means the same as a deviation of +1 from the group mean of 4.82 in group 4. The normalization does not change the fact that relative firm effects within groups are identified but relative firm effects between groups are not identified. It is therefore preferable to correlate only effects of the same group.

[12]This normalization is not exactly implemented in `felsdvreg`, But the program has two options for normalization: The option `normalize` normalizes the firm effects to mean zero within each group and adds the mean firm effects that are subtracted in each group to the person effects. The option `cons` normalizes the person effects to sum to zero over all observations and displays the overall mean person effect as the regression constant. Both options can be combined.

Andrews et al. (2006b) show that the correlation between worker and firm effects is biased and that the bias is greater the lower the observed worker mobility between firms. After estimation one may therefore want to select firm and person effects that fulfill certain minimum requirements with respect to the minimum number of movers per firm or the minimum number of observations per person. This is possible with the variables defined in the options **mnum()** and **pobs()** and returned by `felsdvreg`.

Even though the algorithm described above is memory-saving, some applications in large data sets will still reach the limit of the computer memory available. It is therefore important to observe the following remarks. The memory intensive part of the program runs in Mata. Mata can only use memory which is not allocated to Stata by the -set mem- command. The user should therefore not allocate too much memory to Stata. The error message "unable to allocate real" indicates that Mata is running out of memory. In this case memory allocated to Stata by -set mem- should be reduced. The error message "no room to add more observations / variables" indicates that Stata is running out of memory. In this case the memory allocated to Stata by -set mem- should be increased. If there is not enough memory available to run `felsdvreg` on the complete sample, it might be worthwhile to run it on a sub-sample. In order to maximize the number of identified firm effects in a sub-sample, one could chose sub-samples such that the mobility groups remain intact. For example, one might chose a large mobility group as a sub-sample and remove the remaining groups. In this case `felsdvreg` should first be run with the option **grouponly**. This runs only the grouping algorithm creating the group variable. This variable can be used to chose a sub-sample of the original sample on which `felsdvreg` can then be run.

The program `felsdvreg` can also be used for instrumental variable (IV) estimation in order to cope with endogenous regressors. In order to produce IV estimates, the two stages of the 2SLS (two-stage least squares) estimation have to be carried out manually. In the second stage estimation, `felsdvreg` needs to be told the names of the regressors which have been predicted from a first stage, as well as which original regressors belong to the predicted regressors. For example, say that in a regression of y on z1, x2, x3 and two-way fixed effects the variables x2 and x3 are to be instrumented by the IVs z2 and z3. A 2SLS estimation can be carried out in the following way:

1. Run a first stage regression for x2 and generate its prediction x2hat:
   felsdvreg x2 z1 z2 z3, i(i) j(j) xb(xb) p(phat) f(fhat) [...]
   gen x2hat=xb+phat+fhat
2. Run a first stage regression for x3 and generate its prediction x3hat:
   felsdvreg x3 z1 z2 z3, i(i) j(j) xb(xb) p(phat) f(fhat) [...]
   gen x3hat=xb+phat+fhat
3. Run the second stage regression:
   felsdvreg y z1 x2hat x3hat, i(i) j(j) xb(xb) p(phat) f(fhat) **hat(x2hat x3hat) orig(x2 x3)** [...]

In the second stage regression hat(x2hat x3hat) and orig(x2 x3) tell `felsdvreg` that x2hat and x3hat are first-stage predictions of x2 and x3. This allows `felsdvreg` to adjust the residual sum of squares and the standard errors of the second stage regression (see for example Greene 2003, p.400).

The program `felsdvreg` includes the options of computing robust and clustered standard errors. However, the memory-saving design of the estimation is especially costly in terms of computing time when robust or clustered standard errors are computed. Computing robust or clustered standard errors may in some cases therefore be prohibitively time consuming.

The program `felsdvreg` checks for collinearity between the explicit right-hand-side regressors right at the start. But collinearity between regressors and fixed effects also poses a problem. Sometimes it is easy to avoid regressors that are collinear with the fixed effects. For example, one can easily avoid to include time-constant variables like gender in a model with individual fixed effects. But other cases are more difficult. For example, if school dummies are added as explicit right-hand side regressors to a model including teacher and student fixed effects it is hard to know a priori which school effects are collinear with the teacher and student effects. Such collinearity will only be detected by `felsdvreg` at the moment when the inverse of the moment matrices is computed in order to solve for the coefficient vector. At that step the program uses the Mata function `invsym()`, which automatically drops collinear regressors. This is the advantage of using `invsym()` at that stage. However, `felsdvreg` provides the option **cholsolve** in order to use the Mata solver `cholsolve()`. Using a solver has advantages in terms of precision, but the disadvantage would here be that it does not simply drop collinear regressors but instead fail and issue the error message ”matrix has missing values”[13].

A further option is feffse(varname) allowing to pass a name of a new variable to store the standard errors of the fixed effects of the second effect (firm effect). All options are also described in detail in the help file accompanying `felsdvreg`.

6.5 Conclusion

This chapter has proposed a memory-saving decomposition of the design matrix to facilitate the estimation of a linear model with two high-dimensional fixed effects. This is applicable, for example, to linked employer-employee data sets but it is also applicable to other matched data that allow to estimate multiple-way fixed-effects models, such as linked student-teacher data, etc.

A common way to estimate such a model is to take into account one of the effects by including dummy variables, and to sweep out the other effect by the within transformation (fixed effects transformation). If the number of groups is high, creating and storing the dummy variables can require much computer memory space. The decomposition of the design matrix presented in this chapter reduces the storage requirements. The Stata ado file `felsdvreg` for the memory-saving computation of the fixed effects model has been described. Besides implementing the memory-saving estimation method, the program also implements a grouping algorithm to determine the identified effects and provides useful summary statistics.

[13] `felsdvreg` uses the currently available Mata functions to solve for the coefficient estimates. This is not the most efficient procedure for the present problem, because not only the design matrix (X, F) but also the moment matrix A is sparse. A has zero entries in all cells where there is no direct worker mobility between the row firm and the column firm. For the solution of systems of linear equations involving sparse matrices there are more efficient algorithms than the standard algorithms used here. However, as explained above, the advantage of using `invsym()` here is that regressors collinear with the fixed effects can be handled.

6.6 Appendix

In the above example, $X'_{i^*}F_{i^*}$, $F'_{i^*}F_{i^*}$ and $F'_{i^*}y_{i^*}$ are:

$$
\begin{aligned}
F'_{i^*}F_{i^*} &= \begin{pmatrix} 1/3 & 1/3 & -2/3 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ -1/3 & -1/3 & 2/3 \\ 0 & 0 & 0 \\ \vdots & \vdots & \vdots \\ 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} 1/3 & 0 & 0 & -1/3 & 0 & \dots & 0 \\ 1/3 & 0 & 0 & -1/3 & 0 & \dots & 0 \\ -2/3 & 0 & 0 & 2/3 & 0 & \dots & 0 \end{pmatrix} \\
&= \begin{pmatrix} \phi_{i11} & 0 & 0 & \phi_{i14} & 0 & \dots & 0 \\ 0 & 0 & 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & 0 & 0 & \dots & 0 \\ \phi_{i14} & 0 & 0 & \phi_{44} & 0 & \dots & 0 \\ 0 & 0 & 0 & 0 & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & & \vdots \\ 0 & 0 & 0 & 0 & 0 & \dots & 0 \end{pmatrix}, \qquad (6.15) \\
\phi_{i11} &= (\frac{1}{3})^2 + (\frac{1}{3})^2 + (\frac{-2}{3})^2 \\
\phi_{i14} &= (\frac{1}{3})(\frac{-1}{3}) + (\frac{1}{3})(\frac{-1}{3}) + (\frac{-2}{3})(\frac{2}{3}) \\
\phi_{i44} &= (\frac{-1}{3})^2 + (\frac{-1}{3})^2 + (\frac{2}{3})^2
\end{aligned}
$$

$$
X'_{i^*}F_{i^*} = \begin{pmatrix} x_{i11} & x_{i21} & x_{i31} \\ x_{i12} & x_{i22} & x_{i32} \\ \vdots & \vdots & \vdots \\ x_{i1K} & x_{i2K} & x_{i3K} \end{pmatrix} \begin{pmatrix} 1/3 & 0 & 0 & -1/3 & 0 & \dots & 0 \\ 1/3 & 0 & 0 & -1/3 & 0 & \dots & 0 \\ -2/3 & 0 & 0 & 2/3 & 0 & \dots & 0 \end{pmatrix}
$$

$$
\begin{aligned}
&= \begin{pmatrix} \xi_{i11} & 0 & 0 & \xi_{i14} & 0 & \dots & 0 \\ \xi_{i21} & 0 & 0 & \xi_{i24} & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & & \vdots \\ \xi_{iK1} & 0 & 0 & \xi_{iK4} & 0 & \dots & 0 \end{pmatrix}, \qquad (6.16) \\
\xi_{ij1} &= (\frac{1}{3})x_{i11} + (\frac{1}{3})x_{i21} + (\frac{-2}{3})x_{i31} \\
\xi_{ij4} &= (\frac{-1}{3})x_{i11} + (\frac{-1}{3})x_{i21} + (\frac{2}{3})x_{i31}
\end{aligned}
$$

$$
\begin{aligned}
F'_{i^*}y_{i^*} &= \begin{pmatrix} 1/3 & 1/3 & -2/3 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ -1/3 & -1/3 & 2/3 \\ 0 & 0 & 0 \\ \vdots & \vdots & \vdots \\ 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} y_{i1} \\ y_{i2} \\ y_{i3} \end{pmatrix} = \begin{pmatrix} \upsilon_{i1} \\ 0 \\ 0 \\ \upsilon_{i4} \\ 0 \\ \vdots \\ 0 \end{pmatrix} \qquad (6.17) \\
\upsilon_{i1} &= (\frac{1}{3})y_{i1} + (\frac{1}{3})y_{i2} + (\frac{-2}{3})y_{i3} \\
\upsilon_{i4} &= (\frac{-1}{3})y_{i1} + (\frac{-1}{3}yx_{i2} + (\frac{2}{3})y_{i3}
\end{aligned}
$$

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