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Worker Reallocation across Occupations in Western Germany

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This paper analyzes the determinants of annual worker reallocation across disaggregated occupations in western Germany for the period 1985-2003. Employing data from the German Socio-Economic Panel, the pattern of average occupational mobility is documented. Worker reallocation is found to be strongly procyclical. Its determinants at the individual level are then investigated while controlling for unobserved worker heterogeneity. A dynamic probit fixed effects model is estimated to obtain coefficients and marginal effects. The incidental parameter bias is reduced by the method proposed in Hahn and Kuersteiner (2004). An interesting finding is that workers changing occupation are about 8 to 9 percent less inclined to experience occupational mobility in the subsequent year than workers who do not change. Except for workers with only compulsory education, the impact of age on the probability of occupational change is declining in the level of education. The unemployment rate has a negative effect on the probability of occupational changes, especially for female foreigners.

JEL classification. J24, J44, J62, C23, C25, C81.

Keywords. Dynamic Binary Choice Models, Fixed Effects, Incidental Parameter Bias, Occupational Mobility, Panel Data.

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1. Introduction

This paper studies the evolution and the determinants of worker reallocation across occupations in western Germany over the period 1985-2003. Worker reallocation across employment states, employers and industries has long been of interest to economists.[1] Movement of workers is an important labor market activity as human capital accumulation, wages and promotional gains/losses are mainly determined by worker's choice of sector, firm and labor market status. Moreover, a good understanding of worker flows at the aggregate level allows to analyze issues such as labor market flexibility and the effectiveness of job-worker matching processes i.e. allocation of workers to their most productive use in the economy. It also provides insight on the behavior of labor markets over the business cycle.[2]

Recently, worker reallocation across occupations defined at a very disaggregated level has become a focus of study.[3] A first reason is that occupations at a detailed level provide information about career changes. For instance the International Standard Classification of Occupations (ISCO-88), used in this study, has 9 occupational groups at one-digit, 28 at two-digit and 116 at three-digit. The four-digit level consists of 390 occupational units. Important career changes at this level can be easily missed even at the three-digit level. For instance, the three-digit group *Physicists, Chemists and Related Professionals* includes a variety of occupations such as *Astronomers*, *Meteorologists*, *Chemists* and *Geologists*.

Secondly, a change of occupation would imply a change of technology for the worker whereas this is not necessarily the case for a change of sector or employer. For example, a truck driver may perform the same tasks for different employers in different industries. Recent findings of Kambourov and Manovskii (2009) suggest that an important part of human capital is occupation specific. When occupational tenure is taken into account, tenure with an industry or employer has relatively little importance for the wage a worker receives. More specifically, everything else being constant, five years of occupational tenure is associated with an increase in wages

[1]See, for example, Abowd and Zellner (1985), Blanchard and Diamond (1990), Jovanovic and Moffitt (1990), Farber (1994), Schmidt (1999).

[2]See, for example, Altonji and Shakotko (1987), Topel (1991), Neal (1995), Parent (2000), Fallick and Fleischman (2001), Nagypal (2004), Cardoso (2005).

[3]See, for example, Parrado and Wolff (1999), Kambourov and Manovskii (2004*b*), Burda and Bachmann (2008) and Moscarini and Vella (2008).

of 12 to 20 percent. This result implies that a substantial part of human capital is destroyed when the worker changes occupation.

Analyzing the levels, cycles, trends and determinants of occupational mobility is thus important for understanding various macro and labor economic phenomena. For Germany, a complete analysis has not been conducted. This is surprising as Germany is one of the world's major economies however also suffering from low employment growth and high unemployment rates. Unemployment is high and has been rising from 3.8 percent in 1980 to 11.6 percent in 2003 (see Statistisches Bundesamt). The high German unemployment rate is largely due to individuals suffering long unemployment spells whereas, for example, in the US unemployment is associated with people changing jobs as opportunities appear and dissolve and is of much shorter duration. Heckman (2002) states that one of the main reasons is the inability to rapidly respond to changes in Germany. The regulated German labor markets are characterized by centralized bargaining, high replacement rates (the percentage of earnings an unemployed worker can claim), and high union coverage. Employment protection laws that maintain the status quo make it difficult for firms to respond flexibly to changing market conditions. This study casts more light on the functioning of German labor markets by focusing on worker reallocation across occupations.

For western Germany, Zimmermann (1999) analyzes wage growth, worker movements between firms and within firms using the German Socio-Economic Panel (SOEP) for the period 1985-1991. His study also briefly addresses occupational mobility and its determinants. As occupational mobility is only a part of a more general analysis, many interesting issues are necessarily left open. For instance, his study does not take into consideration the dynamic component of occupational mobility which is an important contribution of this study. Moreover, as discussed in a companion paper, also available in this working paper series (İsaoğlu (2010)), there are substantial measurement errors regarding occupational affiliations that are driven by the survey structure in the SOEP. When instead of yearly averages, only the average occupational mobility for the entire period is presented, as in Zimmermann (1999), these measurement errors are concealed.

Very recently, Burda and Bachmann (2008) investigate the behavior of sectoral and occupational worker flows to assess both the extent and the dynamics of structural change in western Germany. They use the Institute for Employment Research (Institut für Arbeitsmarkt und Berufsforschung (IAB)) dataset for the time period 1975-2001. Their focus is on the gross and net worker flows involving a change of sector/occupation (for workers moving from one employer to another, from unemployment to employment and from nonparticipation to employment). Found occupational mobility patterns considering the employment to employment transitions have similar, level, cycle and trend as the ones presented in this study. Though they do not perform an econometric analysis to uncover the sources of these patterns.

In this study, individual level data from the SOEP for the period 1984-2004 is used. SOEP is ideal to study worker reallocation as it provides detailed information on the type and the time of the labor market transitions. Worker reallocation is considered according to ISCO-88 since this classification has several advantages for the purposes of this study. ISCO-88 was generated with the objective of considering occupational consequences of different technologies, incorporating new occupations and reflecting shifts in the relative importance of occupational groups. Occupations are grouped together and further aggregated mainly on the basis of the similarity of skills required to fulfill the tasks and duties of the jobs. Two dimensions of the skill concept are used: skill level, which is a function of the range and complexity of the tasks involved, and skill specialization, which reflects the type of knowledge applied, tools and equipment used, materials worked on or with, and the nature of the goods and services produced. Skills refer here to the skills required to undertake the tasks and duties of an occupation and not to the education level of the worker.

The analysis starts by discussing the patterns of *gross* and *net reallocation* and the difference between them, namely *churning*, during the sample period. Gross reallocation of employment is defined as the fraction of workers who are employed in two consecutive years and change occupation, at least once, in between. This provides a measure of average worker mobility at the annual level. Net reallocation is one half of the sum of the absolute changes in occupational employment shares. Churning can be seen as a measure of the turbulence in the labor markets. It represents the excess reallocation of employment not explained by the net distribution.

Gross reallocation is found to be strongly procyclical. It follows the Gross Domestic Product growth in western Germany. The expansion of the economy before and during the German unification (October 1990) and the aftermath recession of the 1993 and the following recovery is clearly observed in employment reallocation across occupations as well. Net reallocation is less procyclical. Another interesting finding is that in 1991 the churning is clearly higher than the net reallocation. This reflects the turbulence that the western German labor markets went through after the unification. There is no trend in overall occupational reallocation over the last two decades.

To understand the determinants of gross reallocation, an empirical model of occupational mobility at the individual level is estimated. In such a model, unobserved time-invariant individual heterogeneity has importance as some covariates are decision variables and individual heterogeneity, most of the time, represents variation in tastes or technology. For instance, risk aversion may drive occupational choice. Moreover, individuals are also likely to make other decisions in life such as education or marriage under the influence of this trait. Estimation results may have incorrect implications if this kind of endogeneity is ignored.

Exploiting the panel structure of the dataset, a fixed effects approach is adopted to control for the time-invariant unobserved worker heterogeneity. Correlation between covariates and individual fixed effects is allowed. The model is estimated by maximum likelihood. Additionally, marginal effects can be computed since estimates of individual fixed effects are obtained.

There is a methodological problem involved in using the maximum likelihood method for nonlinear dynamic fixed effects estimation, namely the incidental parameter bias. As first highlighted by Neyman and Scott (1948), replacing unobserved fixed effects by inconsistent sample estimates leads to biased estimates of the other model parameters. This bias arises in maximum likelihood estimation of dynamic linear models as well as in static or dynamic nonlinear models with fixed effects. In this study, a method proposed by Hahn and Kuersteiner (2004) is implemented to address the incidental parameter bias.

Results from the econometric investigation can be summarized as follows. The lagged occupational mobility is found to be statistically significant and negative. Marginal effects suggest that workers who do change occupation are about 8 to

9 percent less inclined to change occupation in the subsequent year compared to workers who do not change occupation in a given year. Moreover, depending on the worker's characteristics, the effect varies from -14 to -2 percent. As expected, the probability of an occupational change decreases with age. For workers with more than compulsory education, the impact of age on the probability of occupational change is declining in the level of education, i.e. although workers become less inclined to change occupation with age, this effect is less pronounced for workers with high education levels. An increase in the regional unemployment rate has a negative impact on the probability of occupational change. Female foreigners are the most affected group by changes in regional unemployment rates with an average marginal effect of -7 percent. The effect for the rest of the population is only around -2 to -1.5 percent.

This paper is organized as follows. The next section describes the dataset. Section 3 provides information on the occupational affiliations in the SOEP. Section 4 documents and discusses the gross and net reallocation as well as churning and Section 5 presents the estimated model and the covariates. Section 6 presents the results from the econometric investigation and finally Section 7 concludes. The Appendix provides the summary statistics of the estimation sample and the estimation results.

2. German Socio-Economic Panel

SOEP started in the Federal Republic of Germany (FRG) in 1984 as a nationally representative longitudinal survey of persons and private households with around 12,000 respondents (Wagner, Frick and Schupp (2007)). For this study, individual level data from the *Residents in the FRG* and the *Foreigners in the FRG* samples for the period 1984-2004 are employed. The latter sample covers persons in private households with a household head from the main foreigners groups of guestworkers, namely Greeks, Italians, Spaniards, Turkish and former Yugoslavians (hereafter *foreigners*), while household heads in the former sample are from German origin (hereafter *natives*). In June 1990, SOEP expanded to the former German Democratic Republic (GDR). The *Residents in the GDR* sample is not employed in this study as the aim is to understand occupational reallocation in competitive labor markets. Observations for persons who moved to the former GDR states or persons who were residing in the GDR before the unification are therefore also excluded from the analysis.

Representativeness of the SOEP is maintained in the following ways. Children within households of the original panel reaching age 16 enter the SOEP. In case of geographical mobility, persons are followed within Germany. Split offs from the initial household remain in the panel as new households. When third persons move into an existing SOEP household they are also surveyed and followed up even in case of subsequently leaving that household. Finally, when there is a successful interview after a drop-out year, respondents are also given a small questionnaire with questions regarding the drop-out year (Haisken-DeNew and Frick (2003)).

Furthermore, SOEP provides detailed information on labor market transitions, e.g. transitions across the labor market states, across firms or within firms. Information on the exact time of these transitions is collected either via directly asking for the month and year of the change or via questions based on a calendar.

There are other German micro datasets that can be employed for analyzing worker reallocation, most notably the Microcensus and the IAB dataset. Microcensus has an ideal representative sample which considers 1 percent of all households in Germany. However, individuals are followed for a maximum of four consecutive years only. Moreover, for confidentiality reasons, the only available classification in the dataset, which is the national occupational classification (KldB), is provided at three-digit level instead of four.

The IAB dataset is a 2 percent random sample of all employees registered with the German social security system over the period 1975-2001. As the aim of the data collection is to provide a social insurance account for each employee, and as substantial legal sanctions are imposed for incorrect or missing notifications, the information provided is very reliable. Occupational information regarding employer changes is provided daily but occupational changes regarding internal mobility are registered late. Therefore, some occupational mobility is not recorded, such as when an employee changes his/her occupation and the match is destroyed before the next annual notification. Moreover due to confidentiality requirements, the IAB dataset is anonymized. The original data contains occupational information at the four-digit KldB level. In order to anonymize the occupational information, the IAB has cut these codes. For instance, Burda and Bachmann (2008) uses the affiliation only with 128 different occupations. Another disadvantage of this dataset is that all civil servants and self-employed persons apart from apprentices as well as employees with earnings below a certain threshold-and therefore not subject to social insurance contributions-are excluded. In 1995, the employees registered with the social insurance system in western Germany accounted for around 80 percent of the total workforce, but the coverage varies over individual occupations and industries (Bender, Haas and Klose (2000)).

3. Occupational Information in the SOEP

SOEP provides three major classifications for occupations, namely KldB, ISCO-88 and CNEF code. The first is the national classification system of the German Federal Statistical Office, the second is the International Standard Classification of Occupations of the International Labor Office (ILO) and the third is the classification is of the Cross National Equivalent File (Burkhauser, Butrica, Daly and Lillard (2000)).[4]

In this study ISCO-88 at the four-digit level is employed. The ILO of the United Nations produced the International Standard Classification of Occupations in 1958 for the first time and then revised it in 1968 and 1988 in order to make international comparisons of occupational statistics feasible and to provide an example for countries developing or revising their national occupational classifications. ISCO-88 is a nested classification of occupations at the four-digit level. It consists of 9 major groups at the one-digit level. Within these 9 groups there are three further levels: 28 major subgroups, 116 minor groups and 390 unit groups, i.e. classification at the four-digit level corresponds to 390 different occupations (ILO (1990)).

The main advantage of the ISCO-88 classification over the others is its structure. ISCO-88 at the four-digit level is based on two concepts: the *job* (kind of tasks and duties executed) and *skill*. Job is the statistical unit classified by ISCO-88 and a set of jobs whose main tasks and duties are characterized by a high degree of similarity constitutes an occupation. The characteristics of the job performed are the basis of any recent occupational classification whereas the logic of classification depending

[4]This file contains variables that are generated according to the same definitions in order to allow comparative studies among the SOEP, the Panel Study of Income Dynamics (PSID) of the US, the British Household Panel Study (BHPS) and the Canadian Survey of Labour and Income Dynamics (SLID).

on skill requirements is a novelty of ISCO-88 compared to other classifications. Dependence on skill requirements does not mean that the skills necessary to perform the tasks and duties of a given occupation can be acquired only through formal education. The skills may be, and often are, acquired through informal training and experience. In addition, it should be emphasized that the focus in ISCO-88 is on the skills required to carry out the tasks and duties of an occupation and not on whether a particular worker having some occupation is more or less skilled than another worker in the same occupation.

This focus on skill requirements of ISCO-88 is important considering recent research finding evidence on the occupational specificity of human capital (Kambourov and Manovskii (2009)). They show that human capital is not primarily employer or industry but mostly occupation specific, e.g. when a truck driver switches industries, say, from wholesale trade to retail trade, or employers, he/she looses less of his/her human capital generated by the truck driving experience than when he/she switches his/her occupation and becomes a hairdresser.

Until 2002, SOEP provided ISCO-68 codes. In 2002, Hartmann and Schuetz re-coded the occupational and industrial affiliations retrospectively (Hartmann and Schuetz (2002)). The aim of this recoding was to update the ISCO-68 to ISCO-88. They went back to the original questionnaires and depending on the responses, re-coded occupations first according to the KldB and then to ISCO-88.

To understand the factors driving occupational reallocation, it is important to have consistent and reliable occupational affiliation data. However, a vast literature documents measurement errors in occupational affiliations.[5] For the SOEP, measurement errors in the occupational affiliations and a correction method are discussed extensively in İsaoğlu (2010).

4. Worker Reallocation across Occupations in Western Germany: Averages, Cycles and Trends

Before analyzing the determinants of worker reallocation at the individual level, further insights can be obtained from observing its aggregate patterns in terms of gross and net reallocation over the last two decades. Gross reallocation is a measure

[5] See, for example, Mellow and Sider (1983), Murphy and Topel (1987), Mathiowetz (1992), Polivka and Rothgeb (1993), Neal (1999), Kambourov and Manovskii (2004*a*), Moscarini and Thomsson (2008), Moscarini and Vella (2008).

of average worker mobility at the annual frequency and considers the fraction of workers who are employed in consecutive years and who change occupation at least once. Net reallocation is one half of the sum of the absolute changes in occupational employment shares.[6] Due to technological progress, occupations continuously receive positive and negative shocks. As a result, some occupations are born and some die. Hence, net reallocation can be seen as representing labor demand. It is computed on the same sample as used for gross reallocation. Also of interest is churning, which is the difference between gross and net reallocation. It represents the excess reallocation of employment not explained by the net distribution and can thus be seen as a measure of the turbulence in the labor markets.

The sample under analysis is chosen such that it represents the workers in a competitive labor market. More specifically, it consists of native and foreigner females and males, aged 18-65, residing in western Germany, working full-time, not working in the government sector, not self-employed or living in the household of a self-employed, and not dually-employed. Table 1 summarizes the sample characteristics. Moves that make workers leave or enter the sample are not included since these occupational changes are typically accompanied by other decisions like starting ones own business or transiting into full-time employment from part-time employment when children start schooling. A more detailed analysis of gross worker reallocation across occupations for different samples regarding age, education, gender, residence etc., is presented in İsaoğlu (2010).

As the aim of this study is to understand why workers change occupations rather than labor market status, only occupational changes from employment to employment without a significant period of unemployment are considered. The advantage of this approach is that decisions of changing occupation and decisions of participation in the employment pool are separated from each other. However this choice also implies that any result of this study hold for the employed workers only.

Figure 1 shows the gross and net reallocation as well as churning across four-digit ISCO-88 occupations for the period 1985-2003. Gross reallocation averages around 5 percent per year. Double changes in a year are also counted in this measure. Such cases are rare (around 2 percent) and they are considered as a single change in the

[6]This measure is used in Jovanovic and Moffitt (1990) for sectoral and in and Kambourov and Manovskii (2004*b*) for occupational mobility.

estimation. However, one should be aware that this figure may be an underestimation of the true average mobility as the occupational mobility at the individual levels is identified conditioning on other types of job or labor market status changes. Net reallocation averages around 2.7 percent per year, which is an important proportion in explaining the total worker reallocation. Churning accounts for about a quarter of the total reallocation.

Findings considering occupational mobility from other studies can be summarized as follows. Kambourov and Manovskii (2004*b*) analyzes the US with the Panel Study of Income Dynamics (PSID) dataset while defining occupational mobility as the fraction of currently employed individuals who report a current occupation different from their most recent previous report of an occupation. For the period 1968-1997, the average occupational mobility of male workers at the 1-digit level is found to be 13 percent. This figure increases to 19 percent at the 3-digit level. Mostly prior to 1984 mobility rates are increasing; in later years they are more stable. Their findings suggest a mildly procyclical average occupational mobility whereas net occupational mobility is countercyclical. Moscarini and Vella (2008) using monthly the US Current Population Survey (CPS) data for the period 1979-2004 present that reallocation of employed men across three-digit occupations averages about 3.5 percent per month and is strongly procyclical. For Germany, Burda and Bachmann (2008) document average occupational mobility, considering employment to employment transitions only during the period 1980-2000. For females and males between age 16 and 29, it amounts to 4.9 and 6.2 percent respectively. It decreases to 2.3 and 3.1 percent for mid-career females and males (age 30-49) and finally to and 0.8 and 0.9 percent for female and male workers in the period before retirement (age 50-64).

A comparison of gross and net reallocation with the Gross Domestic Product growth in western Germany over the last two decades reveals that gross reallocation of workers is strongly procyclical, see Figure 2. Similar analysis for the US also finds that worker reallocation is procyclical.[7] This behavior might seem at odds with a truly Schumpeterian view, in which recessions promote a more efficient allocation of resources by cleansing out bad investments with low productivity and by freeing up resources for more productive uses. This Schumpeterian view is confirmed for

[7]See, for example, Jovanovic and Moffitt (1990), Nagypal (2004), Moscarini and Vella (2008).

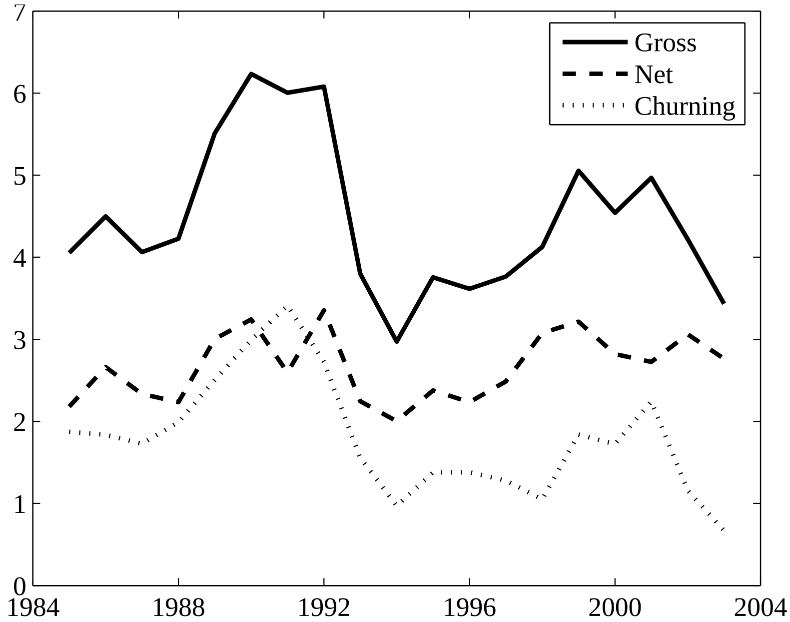

FIGURE 1. Occupational reallocation at the four-digit ISCO-88 level (percentages).

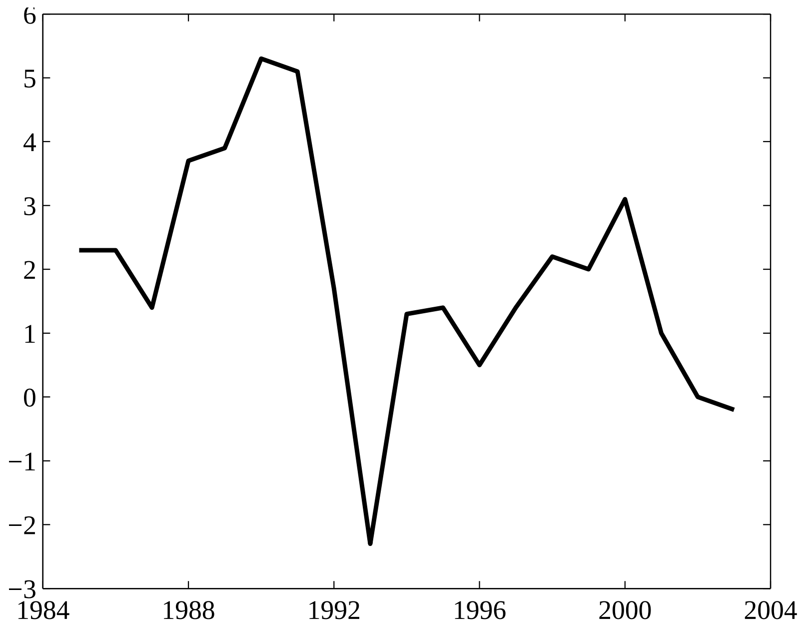

FIGURE 2. Gross domestic product growth in western Germany (percentages).

job reallocation in the manufacturing sector by the work of Davis, Haltiwanger and Schuh (1996), however not for worker reallocation. In fact, Barlevy (2002) allows workers to search on the job as well as through unemployment in his model and shows that during recessions workers reallocate more slowly into their most productive uses. Even though the economy cleanses out its most inferior matches, most workers are stuck in mediocre matches and fewer high quality matches are created. This is because employers create fewer vacancies during recessions which makes it difficult for workers to move.

From the figures it is clear that net reallocation is also procyclical, although it is far less pronounced. Another interesting finding from these figures takes place during the unification period. In 1991, just after the unification, the turbulence clearly surpasses the net reallocation. However, the effect is distributed over the period 1990-1992 for the gross reallocation due to the 1990-1991 economic boom and its effect in 1992. The economic crisis that took place in 1992-1993 is reflected as a huge drop in gross reallocation in 1993-1994. There appears to be no trend in overall occupational mobility.

5. Estimating the Determinants of Occupational Mobility

5.1. Model and Estimation Method. Consider the following empirical model of occupational mobility at the individual level:

$$MOB_{i,t} = \mathbb{1}\left\{MOB_{i,t-1}\gamma_0 + x'_{i,t}\beta_0 + \alpha_i + \epsilon_{i,t} > 0\right\}, \qquad \begin{array}{l} i = 1, \ldots, N, \\ t = 1, \ldots, T(i), \end{array} \tag{1}$$

where N denotes the total number of individuals and since the sample is an unbalanced panel, $T(i)$ the number of periods for person i. $MOB_{i,t}$ is the binary dependent variable which takes value 1 in a given year if the worker changes occupation and 0 otherwise, $\mathbb{1}$ is the indicator function, $MOB_{i,t-1}$ is the lagged dependent variable, $x_{i,t}$ is the vector of other covariates, γ_0 and β_0 are the parameters of interest, α_i is the individual fixed effect and $\epsilon_{i,t}$ is a time-individual specific random shock.

This is an error component model where the error term, $\alpha_i + \epsilon_{i,t}$, is composed of a permanent individual specific term α_i and a transitory shock $\epsilon_{i,t}$. This framework has a particular advantage as it controls for unobserved time-invariant individual heterogeneity. Such heterogeneity is important as labor market outcomes of observably equivalent individuals are markedly different in terms of compensation and employment histories as it is described in the seminal model of Roy (1951).

More recently, Abowd, Kramarz and Margolis (1999) using an employer-employee dataset find that individual effects are statistically more important than firm effects in explaining compensation and performance outcomes. They show that the entire inter-industry wage differential is explained by the variation in average individual heterogeneity across sectors. It is individual effects, not firm effects, that form the basis for most inter industrial salary structure.

If not accounted for, unobserved individual heterogeneity can result in misleading inferences especially when it is correlated with the covariates. In many economic applications, this is the case as covariates are decision variables and individual heterogeneity usually represents variation in tastes or technology. For instance, Guiso and Paiella (2001) show that risk aversion plays an important role in occupational choice. More specifically, they find that it influences the choice of becoming self-employed or public sector employee. Risk averse individuals are also found to choose occupations where large negative income events occur with a relatively low probability. Similarly, it is likely that risk aversion also is important for decisions regarding education and marital status. In order to control for such endogeneity, a fixed effects approach exploiting the panel structure of the data is followed. The individual effect α_i is allowed to be correlated with the covariates $x_{i,t}$. The transitory error $\epsilon_{i,t}$, however, is assumed to be independent of $x_{i,t}$ and independently and identically distributed.

One can expect a negative correlation between job separations and tenure, simply because lower probabilities to change jobs/occupations imply longer periods at the same firm/occupation. On top of this purely statistical relationship, Jovanovic (1979) and Pissarides (1994), among others, find evidence for true state dependency i.e. the probability of change is partially explained by tenure. Thus, one might expect that the probability of occupational change depends on previous changes. For this reason, lagged occupational mobility is included in the estimation as an additional covariate.[8]

There are several models and methods of controlling for unobserved heterogeneity in using panel data (see Chamberlain (1994), Arellano and Honore (2001)). Though, in the specific model presented above, the discrete choice character with

[8]Ideally, one would like to include occupational tenure, however, SOEP does not provide this variable (nor can it be constructed).

the dynamic component restricts the possibilities considerably. A feasible method is random effects as it bypasses the incidental parameters problem by integrating out the individual effects. This method, however, requires strong assumptions: both α_i and $\epsilon_{i,t}$ need to be normally distributed and uncorrelated with the covariates. Although in a recent study Vella and Verbeek (1999) propose a more flexible approach, the distributional assumption of normality cannot be relaxed. Other available estimators usually have some practical limitations, most notably only providing estimates for the primary slope parameters which precludes the computation of the marginal effects (see e.g. Chamberlain (1985), Honore and Kyriazidou (2000)). This is a major drawback as in nonlinear models the objects of interest are in general the effects averaged over individuals rather than the parameters.

In this study, a dynamic fixed effects maximum likelihood approach, where individual effects α_i, $i = 1, 2, \ldots, N$, are considered as parameters to be estimated, is followed. Greene (2002) presents a practical solution that allows estimating nonlinear models with possibly thousands of dummy variable coefficients.[9]

There is a methodological difficulty associated with maximum likelihood estimation of nonlinear and/or dynamic models with fixed effects. In these models, parameter estimates suffer from the incidental parameters problem when individual heterogeneity is left completely unrestricted (Neyman and Scott (1948)). The problem arises because unobserved fixed effects are replaced by inconsistent sample estimates, which in turn leads to biased estimates of the other model parameters. Recently, many studies proposing methods to overcome this problem became available.[10]

To get some intuition for the incidental parameter bias, suppose for the moment that the time horizon is identical for all individuals, so $T(i) = T$ for all

[9]Newton's iterative method is used to find the parameters for which the derivative of the loglikelihood function is zero; the estimates are updated using the inverse of the Hessian and the deviation from zero. When K denotes the number of covariates, the Hessian is an $(N+K)\times(N+K)$ matrix, which makes direct inversion very slow, if at all possible. Computing the inverse is simplified by taking advantage of the sparse nature of the Hessian. The resulting computation than involves matrices of at most size $K \times K$.

[10]See, for example, Lancaster (2000), Hahn and Kuersteiner (2002), Hahn and Kuersteiner (2004), Hahn and Newey (2004), Carro (2003), Fernandez-Val (2007), Fernandez-Val and Vella (2007).

$i \in \{1, \ldots, N\}$. Let $g(y_{i,t}, x_{i,t}; \theta, \alpha_i)$ be the likelihood of obtaining dependent variable $y_{i,t}$ for covariates $x_{i,t}$, when the coefficients are θ and the fixed effect is α_i.[11] The true parameters θ_0 and α_{i0} then satisfy

$$(\theta_0, \{\alpha_{i0}\}_{i=1}^N) = \arg \max_{\theta, \{\alpha_i\}_{i=1}^N} E\left[\frac{1}{NT}\sum_{i=1}^N \sum_{t=1}^T g(y_{i,t}, x_{i,t}; \theta, \alpha_i)\right]. \tag{2}$$

The sample analogue can be written as follows:

$$\hat{\alpha}_i(\theta) = \arg \max_{\alpha_i} \frac{1}{T}\sum_{t=1}^T g(y_{i,t}, x_{i,t}; \theta, \alpha_i), \tag{3}$$

$$\hat{\theta} = \arg \max_{\theta} \frac{1}{NT}\sum_{i=1}^N \sum_{t=1}^T g(y_{i,t}, x_{i,t}; \theta, \hat{\alpha}_i(\theta)). \tag{4}$$

Hence, for a candidate maximizer θ first the likelihood maximizing fixed effects $\hat{\alpha}_i(\theta)$ are computed which are then used in the maximization problem of θ. However, these sample estimates of α_i are inconsistent since there are relatively few observations of each individual in the data, so $\hat{\alpha}_i(\theta_0) \neq \alpha_{i0}$. Since these inconsistent estimates of the fixed effects are used while estimating θ, the coefficients are biased. To see this better, suppose that $N \to \infty$ with T fixed, then the best estimate θ_T of the true parameter is

$$\theta_T = \arg \max_{\theta} \lim_{N\to\infty} \frac{1}{NT}\sum_{i=1}^N \sum_{t=1}^T g(y_{i,t}, x_{i,t}; \theta, \hat{\alpha}_i(\theta)). \tag{5}$$

However, since $\hat{\alpha}_i(\theta_0) \neq \alpha_{i0}$, the estimate θ_T will not be equal to the true parameter θ_0. Only when the number of periods T becomes arbitrarily big, it holds that $\theta_T \to \theta_0$.

There are several ways of addressing the incidental parameter bias. Hahn and Newey (2004) and Hahn and Kuersteiner (2004) consider bias correction of the estimator either by panel jackknife or deriving analytical bias formulas; Woutersen (2002) proposes a correction of the estimating equation and Lancaster (2000) by modifying the maximum likelihood function. In this study the analytical bias correction approach designed for dynamic nonlinear models proposed by Hahn and Kuersteiner (2004) is employed. This method uses that $\theta_T = \theta_0 + \frac{\mathcal{B}}{T} + \mathcal{O}(T^{-2})$ for some $\mathcal{B}$ under smooth moment conditions. For $N \to \infty$, the difference between the

[11] Obviously $y_{i,t} = MOB_{i,t}$ and θ_0 =(γ_0, β_0) in the current model.

real coefficient and its estimate becomes

$$\theta_T - \theta_0 \xrightarrow{p} \frac{\mathcal{B}}{T} + \mathcal{O}\left(\frac{1}{T^2}\right). \tag{6}$$

Hence, when $\mathcal{B}$ is known, the estimator $\theta_T - \frac{\mathcal{B}}{T}$ would be a bias corrected estimator of θ_0. The difference between the static and dynamic bias corrections is that the latter also corrects for covariances over time arising while computing the estimate of the bias.[12]

The main advantage of fixed effects maximum likelihood estimation is that marginal effects can also be computed. However, due to the incidental parameter bias these effects will be biased as well. Using the bias corrected coefficients, Hahn and Newey (2004) also derive a bias corrected estimator for the marginal effects, which is extended for the dynamic case by Fernandez-Val (2007). An additional advantage of this method is that the initial conditions problem discussed in Heckman (1981) is avoided. Hence, there is no need for imposing restrictions on the initial values of the process.

5.2. Covariates. To estimate the determinants of occupational mobility, covariates that represent worker characteristics and macro economic situation are selected. More specifically the employed covariates are dummies for lagged occupational mobility and marital status, a year dummy for 1991, workers' age interacted with their educational attainment, regional unemployment rates interacted with origin-gender background of the worker and dummies for one-digit ISCO-88 occupational groups.

The lagged occupational mobility dummy is employed to investigate the presence of the dynamic effects. The estimation method allows the identification of the true state dependence and serial persistence arising from individual heterogeneity. State dependence refers to the effect that past outcomes might have on the current outcome. Heterogeneity refers to unmeasured variables that influence the current outcome but are themselves not influenced by past outcomes.

The direction in which lagged occupational mobility affects the probability of a current occupational change is not obvious. A positive effect of the lagged occupational mobility dummy is suggested by the job-matching theory. Jovanovic

[12]To estimate these covariances, an average of the sample covariances is computed with the variables at periods $t-1$, t and $t+1$, as advised by Hahn and Kuersteiner (2004).

(1979) argues that separation brings separation. The underlying reasoning is that job separations may force some workers to accept jobs in new occupations, wasting some accumulated occupation specific knowledge, and thus raise expected subsequent separations and mobility. Due to the occupational matching component in productivity, the same mechanism is also relevant for occupational mobility. On the other hand, a negative effect can also be expected due to successful matches. The argument is straightforward: when a worker changes an occupation, he/she thinks that the new occupation is the best available match. Unless the job is not according to expectations, the worker is thus expected to be satisfied with the new occupation. Hence, workers who have changed occupation recently are expected to be less likely to change in the following year. The empirical evidence will cast light on the relative importance of these opposing influences.

To assess the importance of family considerations on the probability of occupational change, a marital status dummy is included in the estimation. Family considerations can be of high importance for various reasons. For instance, having a spouse might limit occupational mobility which necessitates geographical mobility. A potentially interesting job which is far away from the current residence might not be taken when the spouse's own activities/career plans block any residential change.

To see the impact of educational attainment four different levels are distinguished, namely *no degree* (only compulsory education of 7 years), *high school* (secondary education but no further vocational training), *high school with vocational training* (secondary school with apprenticeship or other vocational training) and *college* (college and more). The German Apprenticeship System is a vocational training programme, based on the dual system of *on the job training*, which is provided by the firm, and *school education*, which is provided by the state and takes on average 1 or 2 days a week. In school, apprentices receive not only general education but also schooling specific to their occupation. Apprenticeship is completed in between 2 and 3.5 years. Today, around 60 percent of each cohort in Germany undertake apprenticeship training. In 1990, there were approximately 370 recognized apprenticeship occupations which included both blue and white collar professions. These cover many occupations which require college attendance in the UK and the US (Dustmann and Meghir (2005)). Hence, there is a considerable difference between workers having a high school degree only and those having a high school degree with apprenticeship/vocational training. As the latter have more occupation-specific training background, it is important to consider them as separate groups.

Due to the estimation method, time-invariant variables are not identified as they cannot be isolated from the individual fixed effects. However, one might expect that occupational mobility decisions are affected by workers' education/experience levels as well. Although it would have been optimal to relate the educational attainment levels with actual labor market experience, unfortunately this comes at a cost. SOEP does not provide a readily available experience variable. In theory, this variable can be constructed using biography and calendar files. However, this implies a further drop in the number of observations as biography and calendar information is missing for some individuals. Therefore, age is used instead of experience to see the impact of experience on occupational mobility. Educational attainment dummies are interacted with age to allow the impact of age to differ across the four educational background groups.

Through labor market attachment, origin and gender are expected to have an impact on occupational mobility decisions. DiPrete and Nonnemaker (1997) find for instance that in the US women and non-whites are more affected by labor market turbulence than men and whites. For Germany, it is important to distinguish between natives and foreigners in addition to gender. To not impose equal effects of gender for both natives and foreigners, four origin-gender dummies are employed, namely foreigner female, foreigner male, native female and native male. Due to their different characteristics, regional unemployment is expected to affect these groups differently. A high regional unemployment rate will probably decrease the probability of voluntary occupational changes: workers are less inclined to change occupation since there are fewer vacancies available. So, regional unemployment is taken as a measure of labor market tightness affecting workers' career choices. To measure the extent of its effect, the four origin-gender dummies interacted with regional unemployment rates are included in the estimation. It should be pointed out that regional unemployment rates may not be fully exogenous. There might be some simultaneity bias, i.e. it could be the case that not only occupational mobility depends on unemployment rates but also that unemployment rates depend on the occupational mobility. When occupational mobility is high, i.e. individuals with jobs easily migrate to new jobs, this suggests a high number of vacancies. Eventually this can decrease the average unemployment rate. Although this may have some impact on the results, this type of endogeneity is not addressed in this study.

As discussed above, there was considerable turbulence in the German economy due to the unification which is also suggested by the high level of churning in 1991 (see Figure 1). Thus,a dummy variable is included in the analysis to account for this specific event.

Finally, one may suspect that the occupation itself may have a role in determining mobility decisions. To control for these effects, dummies for the one-digit ISCO-88 occupational groups are included as covariates. These groups are *Professionals*, *Technicians and Associate Professionals*, *Clerks*, *Service Workers and Shop and Market Sales Workers*, *Skilled Agricultural and Fishery Workers*, *Craft and Related Trades Workers*, *Plant and Machine Operators and Assemblers*, *Elementary Occupations* and *Legislators, Senior Managers and Officials*. However, these variables can be endogenous as they are decision variables. More specifically, a time-variant effect can have an impact on the choice of occupation. In this study, this kind of endogeneity is not taken into consideration.

6. Estimation Results

6.1. Fixed Effects Probit Estimates with Hahn-Kuersteiner Bias Correction. Table 2 presents coefficients and marginal effects of the fixed effects probit model where the bias is reduced by applying the method of Hahn and Kuersteiner (2004). Four different specifications are considered to observe the impact of various variables and to see the sensitivity of the estimates. The first column of Table 2 focuses on the impact of worker characteristics on the probability of occupational mobility abstracting from macroeconomic variables. It includes lagged occupational mobility and marital status dummies and four age and educational attainment interaction terms. In the next columns the following variables are subsequently added: four origin-gender variables interacted with regional unemployment rates (Column (2)), the 1991 dummy (Column (3)), and the one-digit ISCO-88 occupational dummies (Column (4)).

The lagged dependent variable has a statistically significant negative effect in all specifications. Results suggest that, compared to workers who do not change occupation in a given year, workers who do change are about 8 to 9 percent less

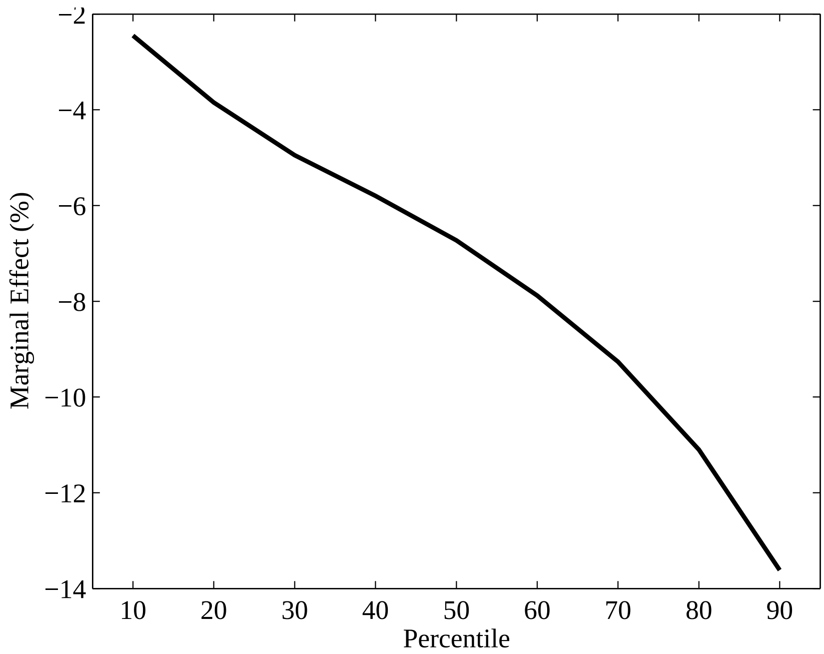

FIGURE 3. The marginal effects of lagged mobility according to percentiles.

inclined to change occupation in the subsequent year. This result is found to be robust across all specifications. The found negative effect contrasts with findings of some recent studies. For example, Moscarini and Vella (2008) construct a pseudo panel based on cohorts to deal with endogeneity and find a positive effect of lagged occupational mobility for the US. This issue will be discussed in detail in the next subsection.

Figure 3 shows the impact of lagged mobility for workers with different probabilities of occupational change. On the horizontal axis individuals are ranked according to their propensities to change occupation; on the vertical axis are the marginal effects. This figure uses the findings of Column (3), which as discussed below, is the preferred specification. The impact of lagged occupational mobility is changing considerably depending on the propensity to change occupation. Workers with the lowest propensity are about 2 percent less likely to change occupation if they have changed occupation in the previous year. This number becomes 14 percent for workers who are most inclined to experience occupational mobility. Therefore, the more a worker is inclined to change occupation based on his/her unobserved fixed effect and other observables, the more important it is whether or not he/she changed occupation in the previous period.

The married dummy is statistically insignificant in all specifications. Other variables that might measure family considerations, such as the number of children in the household, children in the household dummy, home ownership and head of household dummy are all statistically insignificant (results not presented here).

The age of the individual has a different impact on the probability of an occupational change for different educational groups. For workers with only compulsory education, the *no degree* group, there is no statistically significant effect of age. This suggests that these workers with very low educational formation mostly perform tasks for which it does not matter how long they have been in the labor market. In contrast, for the other educational groups, namely *high school*, *high school with vocational training* and *college*, there is a statistically significant negative effect. Between these three educational groups there are differences. In all specifications, age has the most negative effect for high school graduates, then for workers having high school with vocational training and finally for college graduates. So, when workers have more than compulsory education, the impact of age on the probability of occupational change is declining in the level of education: although a higher age makes one less inclined to change occupation, this effect is smaller the higher one's education is. This result is not surprising although one may initially think that workers with high educational attainment do change occupations less often as they receive on average more occupation-specific formal education. Apparently, for aging workers with higher education, their formal background is adapting more easily to new technologies in new occupations so that mobility is relatively higher.

Figure 4 shows the impact of age on workers in different parts of the distribution for each educational group. This figure also uses the findings of Column (3). Clearly, for workers without any degree the effect of age is close to zero over the entire distribution. For other educational groups the order is preserved over the distribution, although there is divergence for the higher percentiles. Moreover, the age effect is becoming more negative. The more a worker is inclined to move, the bigger the impact of age and educational background.

In the second specification, the four origin-gender dummies interacted with regional unemployment rate are added. For all groups, an increase in the regional unemployment rate (measured in percentage points) has a statistically significant negative impact on the probability of occupational change (although the coefficient

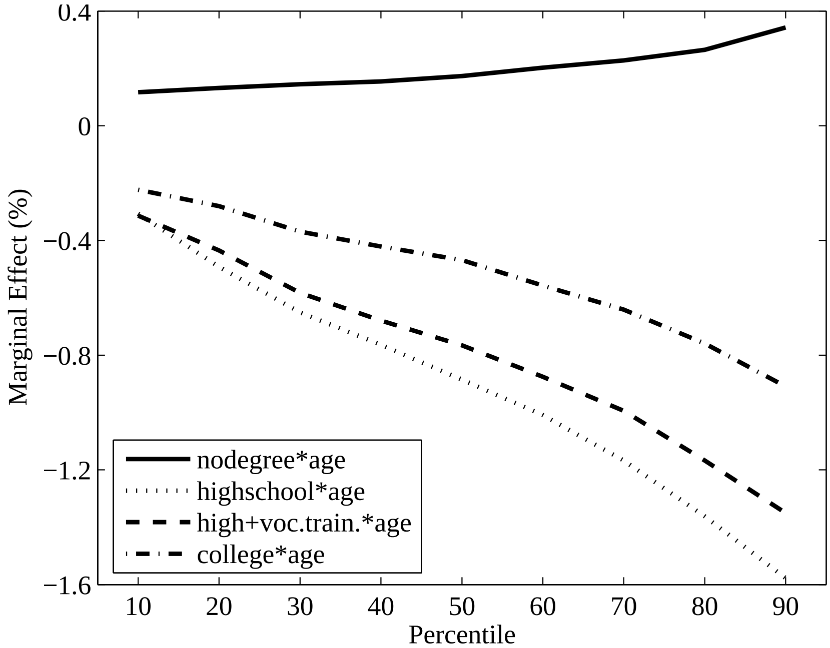

FIGURE 4. The marginal effects of age according to percentiles for the four educational groups.

for *native female*regional unemployment* is not always statistically significant). This is in line with expectations: the higher regional unemployment the lower the number of vacancies so the smaller the probability of changing occupations. The effects depend highly on ones origin and gender. Female foreigners are the group most affected by changes in regional unemployment rates. The average marginal effect is around -7 percent, whereas for the other groups it is around -2.1 to -1.3 percent. Inspection of the data shows that female foreigners are less educated. Although they have no specific reason to be committed to current occupations, their low formal skills may limit the tasks that they can undertake. As the results show, regional unemployment rates affect males less than females, and natives less than foreigners. Note also that the effect of gender depends on the origin and that likewise the effect of the origin depends on the gender. Employing only a gender and an origin dummy would not have captured these distinct effects.

In Figure 5 the effect of origin and gender is shown over the distribution of whole sample. For female foreigners, the effect of regional unemployment rates on the probability of changing occupation becomes more negative when a worker is more inclined to change occupation. This effect ranges from -1 percent to -12 percent depending on the characteristics of the worker. For the other three groups,

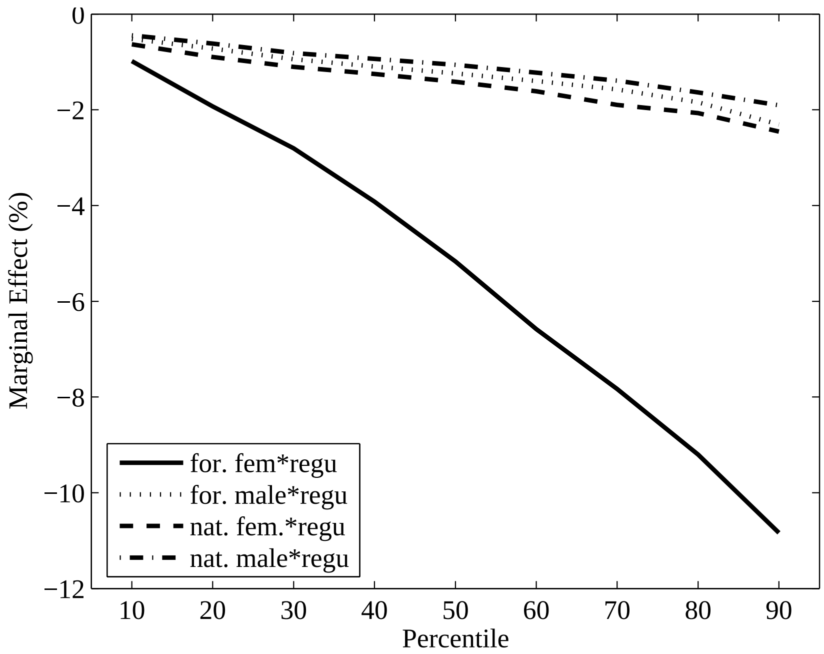

Figure 5. The marginal effects of regional unemployment according to percentiles for the four origin-gender groups.

the effect is also becoming more negative, albeit in a much less pronounced way, namely from -0.5 percent to -2 percent. Apart from female foreigners, the effect of regional unemployment rates does not depend on the individual's unobserved fixed effect and other characteristics.

Although suggested by a higher churning than the net reallocation in Figure 1, the additional turbulence in 1991 after the unification is not confirmed by the estimation results (dummies for the fall of the Berlin Wall in 1989 and the unification in 1990 were also statistically insignificant). However, note that the inclusion of the 1991 dummy mainly affects the origin-gender-regional unemployment interaction variables. For these variables both the coefficients and the marginal effects are less negative. Clearly, taking account of the higher turbulence in 1991 and the accompanying high growth rate reduces the impact of regional unemployment on occupational mobility.

The last column of Table 2 also includes the one-digit ISCO-88 dummies to see the impact of the occupational groups on mobility. The comparison group is *Legislators, Senior Managers and Officials.* Only the *Service Workers and Shop and Market Workers*, *Skilled Agricultural and Fishery Workers*, *Craft and Related Trades*, *Plant and Machine Operators and Assemblers* and *Elementary Occupations* are statistically significant. Although there is no clear ranking, these are the occupations of which the education level is likely to be lowest and most distant from the occupation level of *Legislators, Senior Managers and Officials*. The effect of these group dummies is positive, so, everything else being constant, workers belonging to these occupations have a higher probability of changing occupation. The size of the marginal effects shows that, compared to *Legislators, Senior Managers and Officials*, *Craft and Related Trades* are 17 percent more inclined to change occupation, whereas *Plant and Machine Operators and Assemblers* 18 percent, *Elementary Occupations* 22 percent, *Service Workers and Shop and Market Workers* 23 percent and *Skilled Agricultural and Fishery Workers* 53 percent. The statistically significant different impact can be explained by the intense occupation specific educational investment that workers in the comparison group *Legislators, Senior Managers and Officials* have undertaken which makes changes to other occupations much less likely.

The findings are robust to the inclusion of occupation dummies as results are not considerably affected. However given that these dummies may still be contaminated by some measurement error and because of potential bias stemming from time-variant worker heterogeneity, the specification presented in Column (3) is the preferred one. The presence of fixed effects can be tested with a likelihood ratio test. The null hypothesis of no fixed effects is rejected (probabilities of less than 1 percent).

The results discussed above are obtained after correcting for the incidental parameter bias. To see the size and the impact of these bias corrections, Table 3 presents the results from the uncorrected dynamic fixed effects probit estimations. Comparing the results with and without bias correction reveals that there are only minor differences in terms of statistical significance and no changes of sign for statistically significant variables. In general, there are small differences in the size of the coefficients and marginal effects. The exception is the effect on the lagged occupational mobility dummy. For all the specifications, the uncorrected marginal effects are around -11 percent while the corrected marginal effects are around -8 percent only.

6.2. Robustness. Table 4 presents the results from pooled probit estimation. This model is the most appropriate choice if unobserved time-invariant individual heterogeneity is ignored. To have comparable results, the time- invariant variables are also included in the pooled probit estimation. The first two columns of Tables 2 and 4 are related specifications for bias corrected probit fixed effects and pooled probit respectively. In Column (3) the statistically insignificant variables of origin-gender dummies interacted with regional unemployment rates are removed; in Column (4) the 1991 dummy is added. The latter specification is the preferred pooled probit specification as it is closest to the preferred specification of the probit fixed effects estimation.

The most striking difference between the pooled probit estimates and the bias corrected probit fixed effects estimates is the opposite sign of the lagged occupational mobility dummy. The coefficient changes from about -0.4 to 0.3 and the marginal effect from about -0.085 to 0.025 between these two estimation methods. A further analysis of the data and the implications of the fixed effects method clarifies this puzzling finding.

The data consists of 4,230 individuals for whom both the occupational mobility variable and its lag exist. In probit fixed effects estimation, individual fixed effects are not identified for individuals who change occupation in each period or for individuals who do not change occupation in any period. The sample used for the probit fixed effects estimation consists of 640 individuals. For the remainder of the paper, this sample is referred to as the fixed effects sample and the sample with all workers as the pooled sample. Intuition for the opposite signs of the lagged dependent variable can be obtained by inspecting the different samples.

Table 5 shows how the distribution of current mobility depends on lagged mobility. The upper panel presents this effect for the pooled sample and the lower panel for the fixed effects sample. For example, in 8.3 percent of the cases when a worker changed occupation in the previous year, he/she is changing again in the current year according to the pooled sample. For this sample, workers who changed occupation in the previous year are more likely to change occupation in the current year compared to workers who did not change in the previous year (8.3 and 3.0 percent respectively). This explains the positive effect found in the pooled probit results for this sample. However, for the fixed effects sample the effect is reversed. Workers who changed occupation in the previous year are less likely to change occupation in the current year compared to workers who did not change in the previous year (9.9 and 15.6 percent respectively).

Therefore, change of the sign of the lagged occupational mobility variable is due to the different samples. Of the individuals who are in the pooled sample but not in the fixed effects sample, 99 percent never change occupation. As many observations with no current and no previous occupational mobility are eliminated, there are relatively more workers who have not changed in a given year but changed in the consecutive year. This explains the increase from 3.0 to 15.6 percent for this group when the pooled sample is reduced. Hence, a worker who did not change occupation in a given year is more likely to change in the subsequent year compared to someone who has changed in that given year. In economic terms, there is a considerable group of individuals who are inherent non-movers, i.e. individuals who never change occupation in the sample. Although their non-moving behavior reflects an important feature of the German labor markets, this group is not of help to understand the contribution of true state dependence, worker characteristics and macroeconomic changes.

When comparing the bias corrected fixed effect probit results and the pooled probit results, it is more appropriate to use the same sample, i.e. the fixed effects sample. These results are shown in Table 6. The impact of lagged mobility is now also negative and statistically significant. The coefficient is around -0.35 to -0.37, the marginal effect is around -7 percent. Although more in line with the bias corrected fixed effects probit estimates, the impact of lagged mobility is slightly lower.

It can be argued that the negative effect is largely due to the distribution of workers with respect to the years in the sample. Workers who are in the sample should have at least one occupational change, but many have only one occupational change. Relatively speaking, individuals with fewer observations in the sample have more occupational changes. One might wonder whether this is driving the results. Table 7 shows the distribution of workers according to number of years in the sample. The average period is 8.3 years. In Table 8 results are shown for the same specifications as for the bias corrected fixed effects probit, but for a sample in which workers exist at least six years. Although the marginal effect of lagged mobility becomes about -5 percent, the effect is still statistically significant. The implications for the coefficients and marginal effects of the other covariates is relatively minor.

To see the sensitivity of other covariates to the inclusion of the lagged dependent variable, Table 9 presents the bias corrected fixed effects probit estimates for the static model. The bias corrections are done according to Hahn and Newey (2004). There are slight changes in the size and significance levels of the coefficients and marginal effects, but no changes in signs. Including the lagged mobility dummy has no considerable effects on other coefficients. However, comparison of the loglikelihood values with their counterparts when the lagged dependent variable is included, shows that the dynamic model provides a better specification.

7. Conclusion

In this study, evolution and the determinants of occupational reallocation of workers in western Germany over the period 1985-2003 are analyzed using individual level data from the SOEP. The occupational mobility is considered at the most disaggregated level of ISCO-88 which consists of 390 occupational units. Using this level of disaggregation implies that a moving worker changes career and relocates to a different technology.

Annual average occupational mobility is found to be strongly procyclical. The expansions and recessions of the German economy in the last two decades are accompanied by similar changes in aggregate occupational mobility levels. No trend can be observed in gross reallocation patterns. Net reallocation is found to be procyclical as well, though less pronounced. More interestingly, the turbulence in labor markets that followed unification is clearly observed in the patterns of gross and net reallocation as well as in churning.

To analyze the sources of gross reallocation, a dynamic fixed effect maximum likelihood estimation taking into consideration unobserved time-invariant worker heterogeneity is considered. The incidental parameter bias is addressed accordingly. There are important new findings. The marginal effect of the lagged dependent variable suggests that workers who change occupation in the current year are 8 to 9 percent less inclined to change occupation in the subsequent year compared to workers who do not change occupation in the current year. This is interesting since lagged occupational mobility favors current occupational mobility when worker heterogeneity is ignored. When one also controls for the individual heterogeneity through a fixed effects procedure, workers with identical moving decisions in all periods are dropped. If the interest is the sources of occupational changes not driven by individual heterogeneity, lagged occupational mobility makes a current occupational change less likely. A higher age, as expected, decreases the probability of an occupational change. For workers with more than compulsory education, the impact of age on the probability of occupational change is declining in the level of education, i.e. although a higher age makes one less inclined to change occupation, this effect is smaller the higher ones education is. An increase in the regional unemployment rate has a statistically significant negative impact on the probability of occupational change. This effect is very profound for female foreigners and small for the other origin-gender groups.

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Appendix. Tables

The tables on the following pages present the sample characteristics and estimation results.

variables	mean	sd
age	37.14	9.07
male	0.81	0.39
foreigners	0.27	0.44
married	0.70	0.46
no degree	0.04	0.19
high school	0.17	0.37
high school and vocational training	0.65	0.48
college	0.15	0.35
legislators, senior officials and managers	0.06	0.25
professionals	0.09	0.29
technicians and associate professionals	0.18	0.38
clerks	0.11	0.31
service workers and shop and market sales workers	0.03	0.17
skilled agricultural and fishery workers	0.001	0.02
craft and related trades workers	0.27	0.45
plant and machine operators and assemblers	0.19	0.39
elementary occupations	0.07	0.25
number of observations	5,331	
number of individuals	640	

Table 1. Sample means and standard deviations for the fixed effects sample.

	(1)	(2)	(3)	(4)
lagged mobility	−0.4084*** (0.0723)	−0.4268*** (0.0726)	−0.4279*** (0.0727)	−0.4144*** (0.0737)
	[−0.0840***] (0.0187)	[−0.0868***] (0.0201)	[−0.0869***] (0.0209)	[−0.0844***] (0.0246)
married	−0.0996 (0.0919)	−0.0947 (0.0928)	−0.0930 (0.0928)	−0.0880 (0.0939)
	[−0.0243] (0.0190)	[−0.0230] (0.0191)	[−0.0226] (0.0191)	[−0.0213] (0.0194)
no degree*age	0.0002 (0.0313)	0.0111 (0.0324)	0.0087 (0.0324)	0.0199 (0.0335)
	[0.0000] (0.0072)	[0.0030] (0.0098)	[0.0023] (0.0092)	[0.0053] (0.0122)
high school*age	−0.0525*** (0.0138)	−0.0421*** (0.0143)	−0.0433*** (0.0144)	−0.0394*** (0.0146)
	[−0.0133***] (0.0021)	[−0.0106***] (0.0017)	[−0.0109***] (0.0018)	[−0.0099***] (0.0021)
high school with vocational training*age	−0.0462*** (0.0074)	−0.0393*** (0.0076)	−0.0397*** (0.0077)	−0.0352*** (0.0078)
	[−0.0112***] (0.0010)	[−0.0095***] (0.0012)	[−0.0096***] (0.0014)	[−0.0085***] (0.0016)
college*age	−0.0346** (0.0154)	−0.0274* (0.0157)	−0.0273* (0.0158)	−0.0228 (0.0159)
	[−0.0080***] (0.0012)	[−0.0063***] (0.0009)	[−0.0063***] (0.0009)	[−0.0052***] (0.0011)
foreigner female*regional unemployment		−0.3319*** (0.1134)	−0.3129*** (0.1117)	−0.3243*** (0.1121)
		[−0.0717**] (0.0281)	[−0.0675***] (0.0254)	[−0.0701**] (0.0289)
foreigner male*regional unemployment		−0.0799** (0.0357)	−0.0666* (0.0364)	−0.0639* (0.0366)
		[−0.0188***] (0.0060)	[−0.0156***] (0.0059)	[−0.0149**] (0.0064)
native female*regional unemployment		−0.0766* (0.0450)	−0.0657 (0.0455)	−0.0592 (0.0465)
		[−0.0205***] (0.0055)	[−0.0176***] (0.0060)	[−0.0157**] (0.0067)
native male*regional unemployment		−0.0669*** (0.0216)	−0.0558** (0.0227)	−0.0616*** (0.0231)
		[−0.0161***] (0.0041)	[−0.0134***] (0.0040)	[−0.0148***] (0.0046)
1991			0.1213 (0.0853)	0.1213 (0.0857)
			[0.0310] (0.0214)	[0.0309] (0.0218)
professionals				−0.0016 (0.1983)
				[−0.0004] (0.0401)
technicians and associate professionals				0.1993 (0.1678)
				[0.0514] (0.0447)
clerks				0.2410 (0.1912)
				[0.0639] (0.0538)
service workers and shop and market sales workers				0.7123*** (0.2643)
				[0.2275**] (0.1036)
skilled agricultural and fishery workers				1.4670* (0.7572)
				[0.5361**] (0.2729)
craft and related trades workers				0.6201*** (0.1967)
				[0.1701**] (0.0742)
plant and machine operators and assemblers				0.6354*** (0.2103)
				[0.1823**] (0.0802)
elementary occupations				0.7145*** (0.2283)
				[0.2240**] (0.0952)
Loglikelihood	−1965.4	−1950.7	−1950.1	−1938.7
LR test fixed effects	3015.33*** (χ^2_{639})	3001.34*** (χ^2_{639})	3005.65*** (χ^2_{639})	3024.13*** (χ^2_{639})

Robust standard errors in parentheses, marginal effects in square brackets.
*** significant at 1%; ** significant at 5%; * significant at 10%.

TABLE 2. Fixed effects probit estimates with Hahn-Kuersteiner bias correction (in Column (4) the comparison group is *Legislators, Senior Managers and Officials*).

	(1)	(2)	(3)	(4)
lagged mobility	-0.7507^{***}	-0.7711^{***}	-0.7717^{***}	-0.7567^{***}
	(0.0809)	(0.0812)	(0.0812)	(0.0819)
	$[-0.1152^{***}]$	$[-0.1170^{***}]$	$[-0.1170^{***}]$	$[-0.1147^{***}]$
	(0.0298)	(0.0325)	(0.0337)	(0.0394)
married	-0.1072	-0.1037	-0.1020	-0.0985
	(0.1035)	(0.1043)	(0.1043)	(0.1050)
	$[-0.0216]$	$[-0.0208]$	$[-0.0204]$	$[-0.0196]$
	(0.0211)	(0.0211)	(0.0211)	(0.0213)
no degree*age	-0.0025	0.0093	0.0072	0.0181
	(0.0358)	(0.0370)	(0.0371)	(0.0378)
	$[-0.0006]$	[0.0021]	[0.0016]	[0.0040]
	(0.0074)	(0.0106)	(0.0101)	(0.0130)
high school*age	-0.0582^{***}	-0.0465^{***}	-0.0475^{***}	-0.0435^{***}
	(0.0157)	(0.0161)	(0.0161)	(0.0163)
	$[-0.0122^{***}]$	$[-0.0097^{***}]$	$[-0.0099^{***}]$	$[-0.0091^{***}]$
	(0.0029)	(0.0021)	(0.0023)	(0.0024)
high school with vocational training*age	-0.0506^{***}	-0.0425^{***}	-0.0428^{***}	-0.0385^{***}
	(0.0080)	(0.0082)	(0.0082)	(0.0083)
	$[-0.0102^{***}]$	$[-0.0085^{***}]$	$[-0.0086^{***}]$	$[-0.0077^{***}]$
	(0.0013)	(0.0014)	(0.0016)	(0.0018)
college*age	-0.0378^{**}	-0.0297^{*}	-0.0296^{*}	-0.0256
	(0.0168)	(0.0169)	(0.0169)	(0.0171)
	$[-0.0072^{***}]$	$[-0.0056^{***}]$	$[-0.0056^{***}]$	$[-0.0048^{***}]$
	(0.0016)	(0.0011)	(0.0012)	(0.0012)
foreigner female*regional unemployment		-0.3870^{***}	-0.3694^{***}	-0.3788^{***}
		(0.1159)	(0.1162)	(0.1160)
		$[-0.0674^{**}]$	$[-0.0643^{**}]$	$[-0.0662^{*}]$
		(0.0342)	(0.0321)	(0.0353)
foreigner male*regional unemployment		-0.0911^{**}	-0.0795^{*}	-0.0760^{*}
		(0.0400)	(0.0412)	(0.0417)
		$[-0.0177^{***}]$	$[-0.0155^{**}]$	$[-0.0147^{**}]$
		(0.0067)	(0.0065)	(0.0071)
native female*regional unemployment		-0.0826^{*}	-0.0730	-0.0669
		(0.0492)	(0.0497)	(0.0502)
		$[-0.0183^{***}]$	$[-0.0161^{**}]$	$[-0.0147^{**}]$
		(0.0059)	(0.0063)	(0.0069)
native male*regional unemployment		-0.0759^{***}	-0.0661^{**}	-0.0713^{***}
		(0.0243)	(0.0257)	(0.0259)
		$[-0.0152^{***}]$	$[-0.0132^{***}]$	$[-0.0141^{***}]$
		(0.0045)	(0.0044)	(0.0050)
1991			0.1076	0.1094
			(0.0952)	(0.0956)
			[0.0225]	[0.0228]
			(0.0228)	(0.0231)
professionals				0.0332
				(0.1977)
				[0.0067]
				(0.0411)
technicians and associate professionals				0.1923
				(0.1636)
				[0.0405]
				(0.0424)
clerks				0.2361
				(0.1826)
				[0.0512]
				(0.0502)
service workers and shop and market sales workers				0.7044^{***}
				(0.2463)
				$[0.1819^{*}]$
				(0.0952)
skilled agricultural and fishery workers				1.5353
				(0.9356)
				[0.4677]
				(0.3226)
craft and related trades workers				0.6319^{***}
				(0.1898)
				$[0.1422^{**}]$
				(0.0719)
plant and machine operators and assemblers				0.6470^{***}
				(0.2039)
				$[0.1522^{*}]$
				(0.0777)
elementary occupations				0.7423^{***}
				(0.2148)
				$[0.1902^{**}]$
				(0.0910)
Loglikelihood	-1955.7	-1940.9	-1940.2	-1929.0

Standard errors in parentheses, marginal effects in square brackets.
*** significant at 1%; ** significant at 5%; * significant at 10%.

TABLE 3. Fixed effects probit estimates without bias correction (in Column (4) the comparison group is *Legislators, Senior Managers and Officials*).

	(1)	(2)	(3)	(4)
lagged mobility	0.3205***	0.2992***	0.2998***	0.2973***
	(0.0598)	(0.0601)	(0.0601)	(0.0602)
	[0.0281*]	[0.0257]	[0.0257*]	[0.0255*]
	(0.0150)	(0.0171)	(0.0144)	(0.0143)
married	−0.0668*	−0.0656*	−0.0651*	−0.0661*
	(0.0353)	(0.0365)	(0.0365)	(0.0365)
	[−0.0046]	[−0.0045]	[−0.0044]	[−0.0045]
	(0.0033)	(0.0038)	(0.0034)	(0.0034)
high school	−0.5571*	−0.5751*	−0.5625*	−0.5655*
	(0.3183)	(0.3211)	(0.3192)	(0.3200)
	[−0.0470**]	[−0.0486*]	[−0.0472**]	[−0.0475**]
	(0.0206)	(0.0258)	(0.0213)	(0.0214)
high school with vocational training	−1.0333***	−1.0651***	−1.0523***	−1.0538***
	(0.2962)	(0.2998)	(0.2978)	(0.2987)
	[−0.1498***]	[−0.1564***]	[−0.1533***]	[−0.1535***]
	(0.0251)	(0.0486)	(0.0301)	(0.0303)
college	−0.6407*	−0.7064*	−0.6884*	−0.6873*
	(0.3664)	(0.3691)	(0.3675)	(0.3683)
	[−0.0616*]	[−0.0701*]	[−0.0677*]	[−0.0675*]
	(0.0325)	(0.0397)	(0.0347)	(0.0347)
age	−0.0510***	−0.0498***	−0.0494***	−0.0496***
	(0.0076)	(0.0077)	(0.0077)	(0.0077)
	[−0.0035***]	[−0.0034*]	[−0.0034***]	[−0.0034***]
	(0.0013)	(0.0018)	(0.0013)	(0.0013)
high school*age	0.0154*	0.0147*	0.0145*	0.0147*
	(0.0085)	(0.0086)	(0.0085)	(0.0086)
	[0.0010***]	[0.0010**]	[0.0010***]	[0.0010***]
	(0.0003)	(0.0005)	(0.0003)	(0.0003)
high school with vocational training*age	0.0281***	0.0262***	0.0259***	0.0261***
	(0.0079)	(0.0080)	(0.0079)	(0.0080)
	[0.0019***]	[0.0018**]	[0.0018***]	[0.0018***]
	(0.0005)	(0.0009)	(0.0005)	(0.0005)
college*age	0.0228**	0.0219**	0.0215**	0.0216**
	(0.0096)	(0.0097)	(0.0096)	(0.0096)
	[0.0020***]	[0.0019**]	[0.0019***]	[0.0019***]
	(0.0006)	(0.0009)	(0.0007)	(0.0007)
foreigner male		0.0716	0.1767**	0.1764**
		(0.2474)	(0.0790)	(0.0792)
		[0.0038]	[0.0089]	[0.0089]
		(0.0142)	(0.0066)	(0.0066)
native male		0.1238	0.3072***	0.3057***
		(0.2361)	(0.0784)	(0.0785)
		[0.0079]	[0.0174]	[0.0173]
		(0.0174)	(0.0108)	(0.0108)
native female		−0.1223	0.2258***	0.2235***
		(0.2586)	(0.0841)	(0.0842)
		[−0.0087]	[0.0136]	[0.0135]
		(0.0171)	(0.0093)	(0.0092)
regional unemployment		−0.0567*	−0.0308***	−0.0273***
		(0.0298)	(0.0064)	(0.0066)
		[−0.0039*]	[−0.0021*]	[−0.0019*]
		(0.0021)	(0.0011)	(0.0010)
foreigner male*regional unemployment		0.0153		
		(0.0327)		
		[0.0009]		
		(0.0017)		
native female*regional unemployment		0.0449		
		(0.0331)		
		[0.0034]		
		(0.0023)		
native male*regional unemployment		0.0257		
		(0.0310)		
		[0.0019]		
		(0.0019)		
1991				0.1225**
				(0.0588)
				[0.0091]
				(0.0069)
Loglikelihood	−3473.1	−3451.4	−3452.9	−3450.8

Standard errors in parentheses, marginal effects in square brackets.
*** significant at 1%; ** significant at 5%; * significant at 10%.

TABLE 4. Pooled probit estimates for the pooled sample (the comparison groups are *no degree*, *no degree*age*, *foreigner female* and *foreigner female*regional unemployment*).

	Mob_t	
Mob_{t-1}	1	0
1	8.3	91.7
0	3.0	97.0

	Mob_t	
Mob_{t-1}	1	0
1	9.9	90.1
0	15.6	84.5

TABLE 5. The effect of lagged mobility on the distribution of current mobility for the pooled sample (upper panel) and the fixed effects sample (lower panel).

	(1)	(2)	(3)	(4)
lagged mobility	−0.3493***	−0.3647***	−0.3637***	−0.3695***
	(0.0680)	(0.0684)	(0.0684)	(0.0685)
	[−0.0686**]	[−0.0710]	[−0.0708**]	[−0.0717**]
	(0.0338)	(0.0451)	(0.0358)	(0.0365)
married	−0.0902*	−0.0783	−0.0771	−0.0772
	(0.0483)	(0.0505)	(0.0505)	(0.0505)
	[−0.0203]	[−0.0176]	[−0.0173]	[−0.0173]
	(0.0138)	(0.0149)	(0.0136)	(0.0136)
high school	−0.4284	−0.4997	−0.4960	−0.5119
	(0.4630)	(0.4679)	(0.4661)	(0.4688)
	[−0.1144]	[−0.1348]	[−0.1340]	[−0.1384]
	(0.1041)	(0.1100)	(0.1046)	(0.1048)
high school with vocational training	−0.7371*	−0.8430*	−0.8235*	−0.8321*
	(0.4306)	(0.4365)	(0.4346)	(0.4376)
	[−0.2187**]	[−0.2559**]	[−0.2488**]	[−0.2515**]
	(0.0958)	(0.1099)	(0.0989)	(0.0994)
college	−0.5808	−0.7636	−0.7288	−0.7426
	(0.5215)	(0.5288)	(0.5266)	(0.5293)
	[−0.1509]	[−0.2058]	[−0.1951]	[−0.1988]
	(0.1175)	(0.1296)	(0.1215)	(0.1219)
age	−0.0340***	−0.0349***	−0.0342***	−0.0348***
	(0.0115)	(0.0116)	(0.0116)	(0.0117)
	[−0.0076***]	[−0.0078***]	[−0.0077***]	[−0.0078***]
	(0.0010)	(0.0029)	(0.0013)	(0.0014)
high school*age	0.0083	0.0101	0.0097	0.0105
	(0.0128)	(0.0129)	(0.0129)	(0.0130)
	[0.0019]	[0.0023]	[0.0023]	[0.0024]
	(0.0024)	(0.0024)	(0.0023)	(0.0023)
high school with vocational training*age	0.0161	0.0177	0.0170	0.0176
	(0.0118)	(0.0120)	(0.0120)	(0.0121)
	[0.0036***]	[0.0040**]	[0.0038***]	[0.0039***]
	(0.0013)	(0.0018)	(0.0014)	(0.0014)
college*age	0.0118	0.0159	0.0147	0.0154
	(0.0140)	(0.0142)	(0.0141)	(0.0142)
	[0.0025]	[0.0034]	[0.0031]	[0.0033]
	(0.0022)	(0.0023)	(0.0021)	(0.0021)
foreigner male		−0.3556	0.1040	0.1060
		(0.3744)	(0.1143)	(0.1147)
		[−0.0860]	[0.0216]	[0.0219]
		(0.0826)	(0.0263)	(0.0264)
native male		−0.2850	0.1824	0.1797
		(0.3591)	(0.1122)	(0.1126)
		[−0.0709]	[0.0370]	[0.0365]
		(0.0826)	(0.0294)	(0.0293)
native female		−0.2188	0.2394**	0.2367*
		(0.3935)	(0.1213)	(0.1217)
		[−0.0553]	[0.0539]	[0.0532]
		(0.0926)	(0.0368)	(0.0367)
regional unemployment		−0.0916*	−0.0277***	−0.0216**
		(0.0477)	(0.0087)	(0.0090)
		[−0.0206**]	[−0.0062**]	[−0.0048*]
		(0.0096)	(0.0031)	(0.0027)
foreigner male*regional unemployment		0.0659		
		(0.0512)		
		[0.0143]		
		(0.0092)		
native female*regional unemployment		0.0654		
		(0.0520)		
		[0.0164]		
		(0.0107)		
native male*regional unemployment		0.0666		
		(0.0490)		
		[0.0148*]		
		(0.0088)		
1991				0.2167***
				(0.0813)
				[0.0532*]
				(0.0312)
Loglikelihood	−2175.4	−2167.7	−2168.6	−2165.2

Standard errors in parentheses, marginal effects in square brackets.
*** significant at 1%; ** significant at 5%; * significant at 10%.

TABLE 6. Pooled probit estimates for the fixed effects sample (the comparison groups are *no degree*, *no degree*age*, *foreigner female* and *foreigner female*regional unemployment*).

years	observations	percent
2	59	9.2
3	54	8.4
4	58	9.1
5	53	8.3
6	53	8.3
7	52	8.1
8	45	7.0
9	43	6.7
10	30	4.7
11	32	5.0
12	25	3.9
13	18	2.8
14	23	3.6
15	15	2.3
16	14	2.2
17	20	3.1
18	46	7.2
total	640	100

Table 7. Distribution of the number of individuals for the years in the fixed effects sample.

	(1)	(2)	(3)	(4)
lagged mobility	-0.2423^{***}	-0.2663^{***}	-0.2689^{***}	-0.2493^{***}
	(0.0809)	(0.0816)	(0.0818)	(0.0829)
	[-0.0466^{***}]	[-0.0504^{***}]	[-0.0508^{***}]	[-0.0474^{**}]
	(0.0152)	(0.0160)	(0.0166)	(0.0188)
married	-0.1443	-0.1406	-0.1403	-0.1542
	(0.0988)	(0.0998)	(0.0999)	(0.1015)
	[-0.0312^{*}]	[-0.0302]	[-0.0301]	[-0.0330]
	(0.0189)	(0.0191)	(0.0192)	(0.0206)
no degree*age	-0.0196	-0.0100	-0.0126	-0.0025
	(0.0319)	(0.0331)	(0.0331)	(0.0344)
	[-0.0048^{***}]	[-0.0024]	[-0.0030]	[-0.0006]
	(0.0016)	(0.0042)	(0.0035)	(0.0063)
high school*age	-0.0574^{***}	-0.0474^{***}	-0.0488^{***}	-0.0459^{***}
	(0.0145)	(0.0150)	(0.0151)	(0.0153)
	[-0.0127^{***}]	[-0.0104^{***}]	[-0.0107^{***}]	[-0.0100^{***}]
	(0.0034)	(0.0026)	(0.0028)	(0.0031)
high school with vocational training*age	-0.0418^{***}	-0.0352^{***}	-0.0356^{***}	-0.0315^{***}
	(0.0076)	(0.0078)	(0.0079)	(0.0080)
	[-0.0091^{***}]	[-0.0076^{***}]	[-0.0077^{***}]	[-0.0068^{***}]
	(0.0011)	(0.0012)	(0.0014)	(0.0016)
college*age	-0.0330^{**}	-0.0262^{*}	-0.0262	-0.0207
	(0.0156)	(0.0159)	(0.0159)	(0.0161)
	[-0.0066^{***}]	[-0.0052^{***}]	[-0.0052^{***}]	[-0.0041^{***}]
	(0.0016)	(0.0011)	(0.0011)	(0.0011)
foreigner female*regional unemployment		-0.2898^{***}	-0.2708^{**}	-0.2842^{***}
		(0.1092)	(0.1074)	(0.1083)
		[-0.0545^{**}]	[-0.0509^{**}]	[-0.0535^{*}]
		(0.0269)	(0.0240)	(0.0282)
foreigner male*regional unemployment		-0.0641^{*}	-0.0503	-0.0487
		(0.0371)	(0.0379)	(0.0381)
		[-0.0136^{**}]	[-0.0107^{*}]	[-0.0103^{*}]
		(0.0057)	(0.0057)	(0.0062)
native female*regional unemployment		-0.0768	-0.0651	-0.0619
		(0.0514)	(0.0517)	(0.0531)
		[-0.0171^{***}]	[-0.0145^{***}]	[-0.0137^{**}]
		(0.0046)	(0.0050)	(0.0058)
native male*regional unemployment		-0.0654^{***}	-0.0534^{**}	-0.0586^{**}
		(0.0227)	(0.0240)	(0.0245)
		[-0.0141^{***}]	[-0.0115^{***}]	[-0.0126^{***}]
		(0.0040)	(0.0039)	(0.0047)
1991			0.1277	0.1291
			(0.0933)	(0.0937)
			[0.0292]	[0.0294]
			(0.0221)	(0.0227)
professionals				0.0015
				(0.2204)
				[0.0003]
				(0.0405)
technicians and associate professionals				0.2135
				(0.1869)
				[0.0494]
				(0.0479)
clerks				0.2826
				(0.2145)
				[0.0685]
				(0.0605)
service workers and shop and market sales workers				0.7248^{**}
				(0.3087)
				[0.2161^{*}]
				(0.1196)
skilled agricultural and fishery workers				-2.7790^{***}
				(0.7297)
				[-0.1309^{**}]
				(0.0589)
craft and related trades workers				0.6312^{***}
				(0.2202)
				[0.1575^{*}]
				(0.0826)
plant and machine operators and assemblers				0.6050^{**}
				(0.2389)
				[0.1575^{*}]
				(0.0880)
elementary occupations				0.6223^{**}
				(0.2603)
				[0.1753^{*}]
				(0.1016)
Loglikelihood	-1537.6	-1526.2	-1525.5	-1517.1
LR test fixed effects	3868.87^{***}	3891.65^{***}	3893.05^{***}	3909.86^{***}
	(χ^2_{415})	(χ^2_{415})	(χ^2_{415})	(χ^2_{415})

Robust standard errors in parentheses, marginal effects in square brackets.
*** significant at 1%; ** significant at 5%; * significant at 10%.

TABLE 8. Fixed effects probit estimates with Hahn-Kuersteiner bias correction for a sample with minimum 6 periods of observations per individual (in Column (4) the comparison group is *Legislators, Senior Managers and Officials*).

	(1)	(2)	(3)	(4)
lagged mobility				
married	−0.0962 (0.1022)	−0.0943 (0.1029)	−0.0932 (0.1029)	−0.0903 (0.1038)
	[−0.0230] (0.0213)	[−0.0224] (0.0214)	[−0.0221] (0.0214)	[−0.0213] (0.0216)
no degree*age	0.0018 (0.0359)	0.0105 (0.0370)	0.0091 (0.0371)	0.0193 (0.0378)
	[0.0005] (0.0087)	[0.0027] (0.0111)	[0.0024] (0.0108)	[0.0050] (0.0137)
high school*age	−0.0480*** (0.0157)	−0.0392** (0.0161)	−0.0400** (0.0161)	−0.0360** (0.0163)
	[−0.0120***] (0.0020)	[−0.0097***] (0.0017)	[−0.0099***] (0.0018)	[−0.0089***] (0.0020)
high school with vocational training*age	−0.0415*** (0.0079)	−0.0351*** (0.0082)	−0.0354*** (0.0082)	−0.0309*** (0.0083)
	[−0.0099***] (0.0009)	[−0.0083***] (0.0012)	[−0.0084***] (0.0013)	[−0.0073***] (0.0015)
college*age	−0.0298* (0.0168)	−0.0238 (0.0169)	−0.0237 (0.0169)	−0.0189 (0.0170)
	[−0.0067***] (0.0007)	[−0.0053***] (0.0009)	[−0.0053***] (0.0010)	[−0.0042***] (0.0013)
foreigner female*regional unemployment		−0.2982*** (0.1144)	−0.2840** (0.1147)	−0.2945** (0.1146)
		[−0.0630**] (0.0260)	[−0.0599**] (0.0241)	[−0.0622**] (0.0272)
foreigner male*regional unemployment		−0.0680* (0.0398)	−0.0587 (0.0409)	−0.0567 (0.0415)
		[−0.0155**] (0.0065)	[−0.0134**] (0.0065)	[−0.0129*] (0.0069)
native female*regional unemployment		−0.0604 (0.0485)	−0.0528 (0.0491)	−0.0492 (0.0494)
		[−0.0162**] (0.0069)	[−0.0141*] (0.0074)	[−0.0131*] (0.0078)
native male*regional unemployment		−0.0639*** (0.0240)	−0.0564** (0.0254)	−0.0623** (0.0256)
		[−0.0150***] (0.0044)	[−0.0133***] (0.0044)	[−0.0146***] (0.0049)
1991			0.0825 (0.0934)	0.0843 (0.0939)
			[0.0204] (0.0222)	[0.0207] (0.0224)
professionals				−0.0008 (0.1906)
				[−0.0002] (0.0391)
technicians and associate professionals				0.2076 (0.1581)
				[0.0527] (0.0434)
clerks				0.2740 (0.1763)
				[0.0724] (0.0528)
service workers and shop and market sales workers				0.6962*** (0.2383)
				[0.2219**] (0.0955)
skilled agricultural and fishery workers				0.9561 (0.8953)
				[0.3330] (0.3251)
craft and related trades workers				0.6309*** (0.1838)
				[0.1723**] (0.0726)
plant and machine operators and assemblers				0.6195*** (0.1975)
				[0.1766**] (0.0771)
elementary occupations				0.6835*** (0.2087)
				[0.2127**] (0.0890)
Loglikelihood	−2006.1	−1994.0	−1993.4	−1979.2
LR test fixed effects	366.54*** (χ^2_{639})	377.82*** (χ^2_{639})	380.51*** (χ^2_{639})	403.04*** (χ^2_{639})

Standard errors in parentheses, marginal effects in square brackets.
*** significant at 1%; ** significant at 5%; * significant at 10%.

TABLE 9. Static fixed effects probit estimates with Hahn-Newey bias correction (in Column (4) the comparison group is *Legislators, Senior Managers and Officials*).