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Abstract

Using the German Socio-Economic Panel and a newly available task database for Germany, the evolution of wage inequality, wage mobility, and the origins of wage mobility are studied. Since 2006 the increase in the German wage inequality has markedly slowed down, but there is a steady decline in wage mobility since 2000. In particular, workers in the services sector have ceteris paribus a significantly lower wage mobility than in the manufacturing sector. This result is mainly driven by the decrease of wage mobility in the health care and social services sector. Impact of a worker's unemployment spells and occupation on wage mobility has strengthened over the observation period. Between 2006 and 2013 wage and employment growth have been even polarized, but the routinezation hypothesis can only partially confirmed for wage mobility patterns. Workers who mainly perform manual tasks have a lower wage mobility over the observation period, but workers in cognitive routine occupations show a higher and increasing wage mobility over time compared to manual non-routine workers. In order to examine asymmetries in the effects of basic covariates on a worker's downward and upward wage mobility, multinomial logit estimations were applied. Except for the part-time workers, there are no obvious differences for the remaining covariates.

Keywords: wage inequality, wage mobility, task approach, polarization hypothesis

JEL-No.: J31, J24

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1 Introduction

The distribution of labor incomes and hourly wages has received much attention from policy makers, economists, and the general public in recent decades, since hourly wage and labor income inequality started to increase in the United States in the late 1970s and 1980s (Acemoglu, 2002; Alvaredo et al., 2013; Autor et al., 2008) and in most Western European countries, such as Germany, in the mid-1990s (Card et al., 2013; Dustmann et al., 2009; Gernandt and Pfeiffer, 2007).[1] Several explanations have been developed to explain the increase in wage inequality. Hence, the divergent wage growth along the wage distribution in the United States in the 1980s is caused by the skill biased technical change, which reflects the increase in the relative demand for high-skilled workers, the supply of whom could not keep up (Acemoglu and Autor, 2012; Goldin and Katz, 2007; Katz and Autor, 1999). The diverging trends in wage growth along the wage distribution brought the literature about wage inequality to the nuanced version of the skill biased technical change hypothesis that suggests that the diffusion of computer technology in the production process in the 1990s induced the substitution of routine tasks and complementarity of non-routine tasks (Autor et al., 2003). Whereas the predictions of the routinization hypothesis can be confirmed for the United States in the 1990s (Autor et al., 2006, 2008), no wage polarization has been detected in Germany (Dustmann et al., 2009).

Although the annual dispersion of wages is of particular interest, it is merely the static component of wage development. In order to complete the analysis on wage structure, changes in the relative wage position of workers have to be taken into account. Friedman (1962) and Shorrocks (1978) already pointed out that wage mobility can be interpreted as an equalizer of workers' long-term wages, since the movements of individuals along the wage distribution smooth their wage fluctuations over time. In general, research on wage mobility can be arranged in three groups (Riphahn and Schnitzlein, 2016). The first group employs covariance structure models in order to decompose the trend in a worker's wage into the permanent and transitory component (Baker and Solon, 2003; Gottschalk and Moffitt, 1994; Myck et al., 2011). The second group provides evidence for wage mobility over time, across countries, or across different sub-groups of a country. In order to analyze the last, decompositions of the wage mobility for different types of income or wage (Chen, 2009), for specific sub-samples (Aretz, 2013; Gangl, 2005; Van Kerm, 2004), or for a differentiation in a between-group and a within-group component (Bachmann et al., 2016; Buchinsky and Hunt, 1999) were undertaken. Employing a decomposition of the variance in wage mobility in Germany over time, Riphahn and Schnitzlein (2016) show that the decline in wage mobility in the 2000s was mainly driven by structural shifts, i.e. changes in the returns to particular individual characteristics, instead of by the compositional changes of workers. The third group investigates the socio-economic and demographic determinants of individual wage or

[1] A worker's income includes both labor income and capital income. Since the study analyzes the development of hourly wages, the term "income" always refers to labor income and the term "wage" refers to hourly wages based on labor incomes, unless otherwise stated.

income mobility. These studies commonly use a basic set of individual determinants which are based on the covariates of the extended Mincer equation (Mincer, 1974) and build on the human capital model (Mincer, 1958). Since wage growth is originally a measure of structural mobility, Raferzeder and Winter-Ebmer (2007) analyze a worker's change in his or her relative income position based on the difference between his or her income rank in the base year t and the reporting year $t+s$. Based on Austrian income data between 1994 and 2001, they notice that the initial income percentile has a strong influence on a worker's wage mobility. In turn, Gernandt (2009) applies the same approach to West German data on workers' hourly wage mobility between 1984 and 2007 and receives similar results. In contrast, Finnie and Gray (2002) use a hazard model framework to analyze transitions between income quintiles in Canada in the 1980s and 1990s. Therefore, their measure of mobility can be interpreted as the conditional probability of transiting between quintiles. Furthermore, this enables the consideration of duration dependence, since a worker's probability of moving diminishes with the time he or she spent in a given quintile. The authors discover a strong decline in the baseline hazard rate, which indicates that there is high state dependence in both directions along the income distribution. Moreover, Bachmann et al. (2016) employ multinomial logit models to analyze whether there are asymmetries in the coefficients between upward and downward income mobile workers.

This study is related to the second and third group described above. Employing uncensored survey data on hourly wages in Germany for an observation period of 30 years, the contribution to the literature on wage inequality and wage mobility is threefold. First, the development of wage inequality and wage mobility in West and East Germany is illustrated and updated for the past three decades. Second, the origins of a worker's wage mobility are examined, with an emphasis on the change in the importance of certain determinants over time. Third, the impact of different tasks and task intensities in occupations on the workers' wage mobility is investigated more closely by employing a newly available task database for the 2000s and 2010s. The descriptive evidence shows that the commonly observed increase in wage inequality in the 1990s and 2000s can be confirmed. However, wage inequality has started to stabilize in West and East Germany since 2006. Investigating the development in more detail uncovered a decrease of the 5/1 decile ratio and a polarization of wage growth along the wage distribution after the Hartz reforms. In contrast, the Shorrocks wage mobility has been decreasing since the beginning of the 2000s. This is also true for years with stagnating wage inequality. In 2010, the contribution of wage mobility to the reduction of long-term inequality has fallen to 4.8 percent. Applying a decomposition of the change in wage inequality over time reveals that there is a steady decline in the progressivity of wage growth and an overcompensating impact of wage mobility over pro-poor growth in wages. As the 9/5 wage decile ratio has increased more strongly since 2000 in West Germany, the increase in wage mobility in that period might be due to a stronger reranking in the middle of the wage distribution. Introducing a new aggregate measure of state dependence based on wage mobility estimations shows that the persistence of relative wages is also reflected in an

increasing state dependence on initial wage ranks over time for both West and East Germany.

Therefore, the decline in intragenerational wage mobility and the increase of state dependence incite the following question: what determines a worker's wage mobility and did the impact of socio-economic and demographic characteristics change over time? The empirical results evince that worker's educational attainment, gender, labor market status, unemployment spells, firm size, place of residence, and occupations have a strong influence on his or her wage mobility. In particular, the length of unemployment spells within the fixed time windows and the kind of occupation have risen in importance, whereas the influence of gender, living in East Germany, and working part-time has decreased over time. Therefore, the impact of the depreciation of human capital during unemployment on a worker's re-entry wages has been strengthened over time. Contemporaneously, workers' wages depend more strongly on their occupation-specific human capital. Since wage growth has been polarized between 2006 and 2013, a consequential follow-up question is whether this pattern is attributable to the predictions of the nuanced skill biased technical change hypothesis according to Autor et al. (2003). Employing tasks and task intensities of workers' occupation has been neglected in the analysis of hourly wage mobility so far. This is, to the best of my knowledge, the first study that combines the task-based explanations of wage growth with wage mobility estimations. Utilizing a newly available expert database by Dengler et al. (2014), four key findings can be identified. First, there is a polarization of wage and employment growth along the skill distribution between 2006 and 2013. Second, contrary to the routinezation hypothesis, the employment shares of cognitive routine and manual routine tasks take an opposite development in the upper tail of the skill distribution. Third, workers who perform mainly manual tasks have a lower wage mobility over the entire observation period. Fourth, workers in cognitive routine occupations show a higher and also increasing wage mobility compared to manual non-routine workers. Therefore, the prediction of the task-based explanations of wage development can only partially confirmed. Manual routine workers are stronger represented in the middle of the skill distribution, experience wage losses, and suffer losses in wage mobility. However, workers who perform mainly manual non-routine tasks do note differ in their wage mobility from workers in manual routine occupations over the entire observation period. In turn, cognitive routine workers are over-represented at the upper end of skill distribution, experience wage gains and benefit from an increasing wage mobility. In order to uncover asymmetries in the impact of the basic covariates on a worker's downward and upward wage mobility, multinomial logit estimations complete the study. The results show that the convergence of part-time and full-time workers in wage mobility over time is mainly driven by the convergence in their impact on upward mobility. A worker's unemployment duration has a greater impact on downward mobility than on upward mobility and job changes have a significant impact on downward mobility, but no impact on upward mobility.

The rest of the paper is organized as follows: Section 2 presents the data sources of employed variables. Section 3 gives descriptive evidence on wage inequality and mobility in

West and East Germany based on different measures and concepts. Section 4 shows the basic results of wage mobility regressions and empirical extensions using a more detailed industry categorization. Furthermore, the influence of a worker's initial rank on wage mobility and an aggregate measure of state dependence are estimated. Subsequently, the impact of task types and task intensities on wage mobility are investigated. Additionally, differences in downward and upward mobility are examined. Finally, Section 5 concludes.

2 Data

In order to examine the intragenerational wage mobility empirically, suitable individual data are required for a person at least two times. For this purpose, the German Socio-Economic Panel (GSOEP) is used (Wagner et al., 2007). The GSOEP provides information on the socio-economic and the demographic characteristics of each households member as well as on some features of the household as a whole. Since the interviews are conducted annually, household members can be tracked over several years so that the development of their incomes, wages, and other peculiarities can be accurately observed. With respect to the calculation of hourly wages, there are some advantages of the survey data compared to administrative, such as the LIAB. First, the individual labor incomes are not censored by the social security contribution ceiling. Therefore, the whole wage distribution can be observed and part-time workers can be taken into consideration. Second, the GSOEP includes information on contractual working hours as well as on effective working hours, which enables overtime work to be taken into account in the calculation of hourly wages (Grabka, 2014). Third, in contrast to administrative data, which normally includes daily wages, hourly wages can be directly computed based on an individual's monthly labor income and weekly working hours.

The analysis is based on individual labor income data from 1984 to 2014 and restricted to persons between the age of 25 and 60 for each employed time window. On the one hand, persons under the age of 25 are usually in schooling or vocational training. Thus, they do not earn regular labor income. On the other hand, persons above the age of 60 may be already retired or may strongly adjust their working hours due to early retirement programs. Therefore, students, trainees, employees in partial retirement, and retirees are dropped from the sample. Furthermore, civil servants and self-employed persons are not considered, since the former experience a strongly state-regulated wage development and the latter provide only imputed labor income. Thus, the analysis is based on the dependent labor force of the private sector, where workers in marginal or irregular employment are also removed from the sample.[2] To compute the real hourly wage, information on the individual gross monthly labor income and weekly working hours are used. In turn, working hours refer to an individual's effective working hours per week.[3] If there is no data on effective working hours or the extent of effective hours exceed the values of contractual working hours, the

[2] In order to avoid distortions in the calculations and estimations, employees in sheltered workshops, military service, family workers, and other non-employed persons are excluded from the analysis.
[3] Note that the working hours are censored at 80 hours per week.

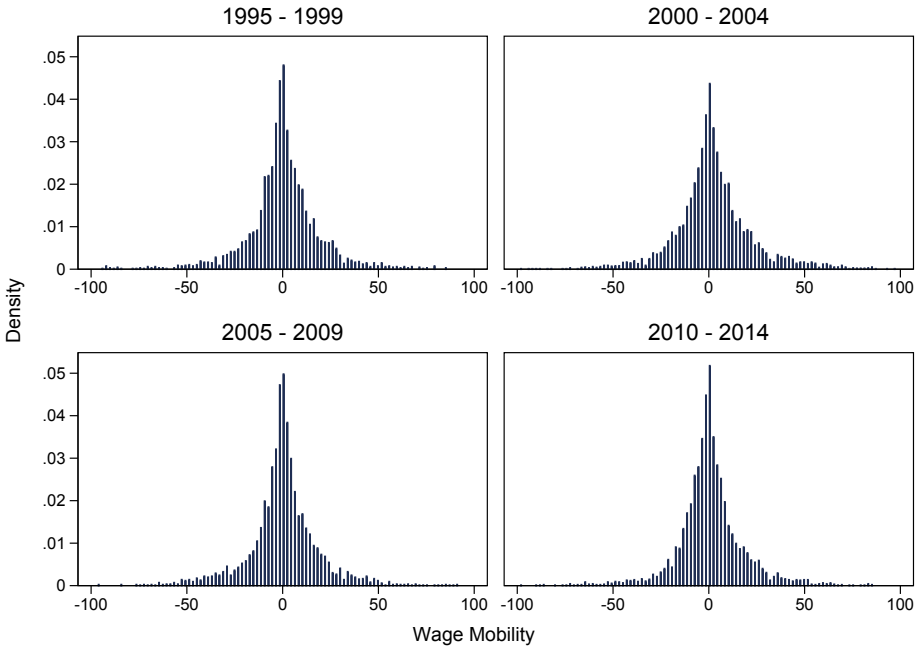
latter is used instead. This procedure ensures that overtime work is taken into account as well as an individual's payment due to the contractual working hours if he or she reports less or no effective working hours. Ultimately, the division of the gross monthly labor income by monthly working hours, which equal weekly working hours times 4.2, yields the nominal hourly wage. For the calculation of the real hourly wage, the nominal wages are deflated to 2010 using the German Consumer Price Index, whereby separate indices are used in East and West Germany between 1991 and 2000 to account for reunification effects. In order to prevent distortions in the estimation due to misreporting gross monthly labor income and working hours, workers reporting real hourly wages less than 1 euro or more than 150 euros as well as reporting working hours less than 4 hours are excluded. Since the purpose of the study is to analyze wage mobility, an appropriate time span between two valid observations of a person's hourly wages has to be defined. If the time period is too short, the development and adjustments of a person's wages cannot be accurately observed. However, the longer the time span is, the higher the probability of panel attrition that may be correlated with certain individual characteristics. In line with the empirical literature, a 4-year time period is conducted in the estimations (Gernandt, 2009; Riphahn and Schnitzlein, 2016). Thus, workers have to be employed in the base year t and the reporting year $t+s$ as well as show valid real hourly wages at both ends of the time span. Nevertheless, individuals have to meet the age restrictions across the time period and show a valid labor market status (employed or unemployed) in the meantime. The latter enables the consideration of unemployment spells in the estimations.

In the empirical literature, individual wage mobility mob_i is commonly defined as the difference in a worker's wage position in the the reporting year $t+s$ and the base year t, measured in percentiles pc (Gernandt, 2009; Riphahn and Schnitzlein, 2016):

$$mob_i = pc_{i,t+s} - pc_{i,t} \tag{1}$$

Thus, wage mobility can take values between -99 and +99. Due to the large definition set of the dependent variable, applying ordinary least squares regression is appropriate. Furthermore, the calculation of percentiles is based on longitudinal weights to account for panel attrition and to enable inference. Since the employed samples have to be balanced, for each worker moving up along the wage distribution, there must be another worker moving down. Therefore, the average wage mobility in a given time window equals zero. The majority of the workers show an upward or downward mobility of about ten ranks within the 4-year time periods (see Figure 1). In the reunified Germany, there is a trend towards a more compressed distribution of rank changes over time. The standard deviation of the relative rank changes decreases from 20.01 in the base year 2000 to 17.15 in the based year 2010. Since a lower standard deviation indicates that there is less variation in the data, there is a first indication for a decreasing wage mobility in Germany since the beginning of the 2000s. Furthermore, there is slightly more upward mobility than downward mobility in employed 4-year time periods. Since a worker's real hourly wage must be observed in both

Figure 1: Distribution of changes in relative rank positions



Notes: Calculation of ranks is based on frequency weights.

the base year and the reporting year, a positive selection towards those workers who have more stable employment situations might occur. Therefore, the estimations might be biased if the selection which is based on the labor market participation of workers in the reporting year is not random and correlates with observed or unobserved individual characteristics of the positively selected groups (Heckman, 1976). However, using a worker's marital status and the number of kids in his or her household as sufficient additional covariates of the selection equation, the application of Heckman selection models yielded no significant selection bias in almost each year, except for 1996 and 2006.[4]

Taking all employed 4-year time period samples together, there are 100,265 person-year observations in the data.[5] The basic set of covariates includes plenty of a worker's socio-economic and demographic characteristics which might affect his or her wage mobility. In turn, these predictors can be divided into three groups. First, *individual characteristics* are important drivers of the wage mobility. Thus, a worker's age, gender, educational attainment, and migration background may influence his or her wage development.[6] These variables are measured in the base year t. In order to avoid a distortion of the estimation results, a worker's initial rank is taken into account, since a low-wage earner cannot descend further along the

[4]Marital status and number of kids are commonly used in wage regressions as selection variables, since they should have no direct effect on wages, but they might determine the labor market participation decision of workers. Estimates of the error term correlation are given in Table 6 in the Appendix

[5]The number of valid wage mobility observations for each 4-year time period is given in Table 4 in the Appendix.

[6]The education variable consists of three categories: "low-skilled", "medium-skilled", and "high-skilled". Its design is based on the CASMIN classification (König et al., 1987) and described in detail in Table 5 in the Appendix.

wage distribution, whereas a high-wage earner cannot rise further. Second, *job stability* is typically associated with wage mobility. On the one hand, job changes can be accompanied by wage increases if employees harness lucrative outside options. On the other hand, a longer job tenure may lead to higher wages through learning curve effects and a longer accumulation of firm- and industry-specific human capital. The latter might also reason the difference in wage mobility between part-time and full-time workers. In turn, experiencing unemployment during the given time period can cause workers to return to the labor market at lower wages due to the depreciation of their human capital. Thus, the following three factors of job stability are taken into account: an indicator whether workers changed their job within the time period, an indicator whether a worker is part-time employed, the number of unemployment spells in the meantime, and the job tenure in the base year t. Third, *employment characteristics* are relevant to wage mobility through different mechanisms. In particular, unions can have a strong impact on workers' wage development if they have sufficient bargaining power. Since they are more strongly represented in larger companies, their wage claims may be higher in these firms. In 2014, 82 percent of workers employed in companies with more than 1000 employees received union wages, whereas only 20 percent of workers employed in companies with less than 50 employees obtained union wages (Federal Statistical Office, 2016). Furthermore, a worker's industry and occupation became more important due the increased relevance of industry-specific human capital (Firpo et al., 2011), the skilled biased technical change (Acemoglu and Autor, 2011), and increased specialization. Moreover, Gottschalk and Moffitt (2009) point out that the transfer of human capital between employment has become more difficult over time. In order to approximate these mechanisms, the following predictors are used: a worker's industry, and occupation, and size of his or her firm in the base year t as well as indicators whether a worker changed his or her industry and occupation in the meantime. Ultimately, an indicator whether a worker lives in East Germany in the reporting year $t+s$ is taking into account, in order to control for regional developments, such as unemployment and GDP growth, and for the different labor market circumstances in West and East Germany.

Based on the nuanced skill biased technical change hypothesis according to Autor et al. (2003), this study examines whether the performance of particular tasks in occupation has an impact on a worker's wage mobility. Since wage growth in occupations determines workers' movements along the wage distribution, the impact of tasks carried out in the base year of the time windows on a worker's wage mobility will be examined in more detail.[7] For this purpose, a newly available measurement method for the operationalization of tasks based on the expert database BERUFENET of the German Federal Employment Agency is applied (Dengler et al., 2014). Using expert knowledge about occupations' or professions' usual work activities in order to sort them into broad task categories is a well-established method in US research about wage growth. In German research on wage growth, survey data,

[7] Since the task intensities and types of some occupations cannot be calculated due to compatibility problems, some observations are lost in the analysis. In order to prevent the loss of more observations by employing 4-year time periods, the time windows are shortened by one year.

without exception, has been used so far to carry out an operationalization of occupations or professions. However, expert databases have several advantages over survey data, such as the BIBB-IAB or BIBB-BAuA employee surveys. First, survey respondents describe the activities they usually perform in their jobs, whereas experts assess which competences and skills are usually attached to a particular profession or occupation. Thus, the latter is a more objective assessment of the tasks in a profession or occupation, independent of a worker's industry or firm size. Second, survey responses can result in a larger variance in the measurement of tasks within and between occupations, since respondents describe their individual tasks which can vary widely for some occupations. Furthermore, error coding in the assignment of occupations during the interview can increase the variance. Third, surveys can only assign tasks to those occupations or professions which are already observed in the data. Therefore, rare or unrepresented occupations are not considered, which can lead to a distortion in the various task intensities of the labor force (Dengler et al., 2014). The expert database includes nearly all job titles used in Germany and link these job titles to approximately 3900 separate occupations. Following Spitz-Oener (2006), five task dimensions are differentiated, in order to ensure comparability with previous task operationalization which were based on survey data for Germany: (1) analytical non-routine tasks, (2) interactive non-routine tasks, (3) cognitive routine tasks, (4) manual routine tasks, and (5) manual non-routine tasks. Since Autor et al. (2003) subsume analytical and interactive tasks under abstract tasks, the employed five task dimensions are in line with the task operationalization in the United States literature. Furthermore, the differentiation between routine and non-routine tasks is based on the substitutability of work activities by machines or computers. Thus, routine tasks follow certain programmable algorithms or rules, whereas non-routine tasks are supported and not replaced by computers or machines. Manual tasks, in contrast to analytical, interactive, and cognitive tasks, are work activities that are performed by hand. In order to calculate an occupation's *task intensities* and *main task type*, an occupation's core requirements given by the experts are used. Since there are five task types, five task intensities are calculated for each occupation, where an occupation's task intensities add up to one. Thus, an occupation's task intensity gives the share of core work activities which can be attributed to the corresponding task, e.g. an analytical task intensity of 0.25 means that a quarter of the work activities in the occupation are analytical in nature. The task type with the highest intensity or share for each occupation is defined as main task type.[8]

Occupations' main task type and task intensity are based on the 3-digit code of KldB 2010 classification. Since the GSOEP does not provide information on a respondent's KldB 2010 level 3 occupation until 2014 and reported respondents' occupation based on the 5-digit code of KldB 1992, which is the previous version of occupational classification, the information on the latter are converted into KldB 2010 level 3 according to official conversion tables.[9]

[8] A detailed description of the calculation method and the database can be found in Dengler et al. (2014).

[9] According to the official conversion tables, some KldB 1992 level 5 occupations cannot be uniquely matched to KldB 2010 level 3 occupations. This entails a loss of around 17.5 percent of observations in each 3-year-time period. Various matching procedures have been applied in order to the reduce the loss of observation, though they yielded very similar results. Therefore, the estimations are carried out based on uniquely matched

Based on the KldB 2010 level 3 occupations, the task information for 2011 are matched to the individual data of workers between 2000 and 2014. The assumption that occupations' task intensities from 2011 are valid for the entire observation period from 2000 to 2014 can be justified twofold. First, occupations do not experience changes in their task compositions on an annual basis. Thus, the adjustment of tasks and work activities takes place slowly over time and depends on the introduction of new technologies. Since computerization of production already mature at the end of the 1990s (Autor, 2015; Beaudry et al., 2016), it can be assumed that task composition of occupations have been relatively stable in Germany since 2000. Second, the task information is based on experts' evaluation of occupations' core requirements, which follow institutionally codified requirements profiles. Thus, an occupation's main task type and task intensity change only slowly over time when data on experts' assessment are applied.

3 Descriptive Evidence

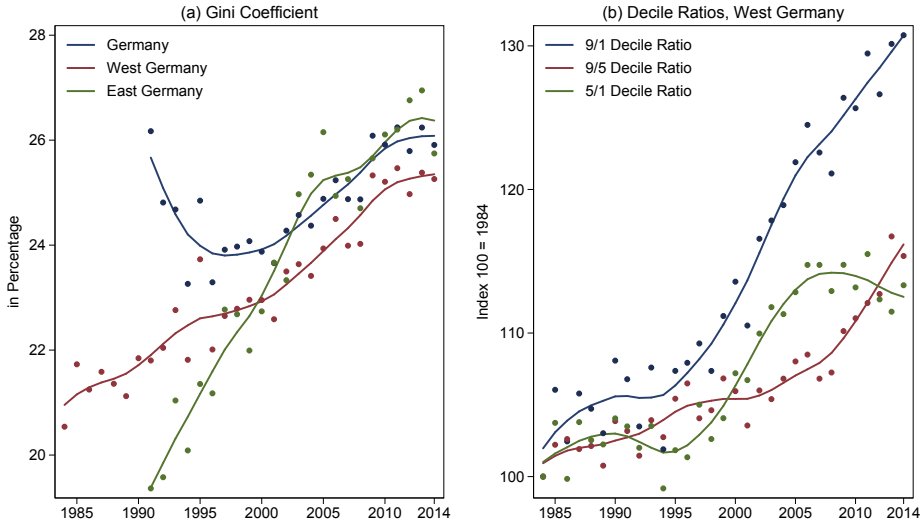
The individual determinants of wage mobility as well as the development of the overall wage mobility within a country are of particular interest in the empirical literature. Measuring the wage mobility in more aggregate levels allows for the investigation of the development of an average workers' wage mobility over time in a country or in particular subgroups. Since a worker's downward and upward mobility depends on his or her wage increases or losses as well as on the wage changes of the other workers in the country, there is a mechanical link between wage mobility and wage inequality. Therefore, the development of wage inequality and wage mobility for Germany between 1984 and 2014 is described below.

3.1 Wage Inequality

There has been a sprouting interest in wage inequality in Germany as well as in most industrialized countries since the 1990s. After the German reunification and the collapse of the Soviet Union, the impact of globalization and the skill biased technical change on the development of the national labor markets increased, which was accompanied by changes in wages and the unemployment rate. Thus, taking a closer look at the development of the wage inequality in West Germany in the 1980s, there are merely moderate increases in the Gini coefficient (see Figure 2, panel (a)). However, wage inequality has increased more strongly since the end of the 1990s. In turn, East Germany has experienced a strong growth in wage inequality since the start of data collection in 1991. Whereas wage inequality was 19.4 Gini points in 1991 and below the West German value of 21.8 at that time, the East German values are above the West German ones since 2001. Interestingly, in the first years after the reunification, the overall wage inequality was initially higher than both regional wage inequality values, decreased in the subsequent years, and then has been increasing again

occupational data. Estimation results based on matching procedures which match occupations based on likelihoods are available upon request.

Figure 2: Development of real hourly wage inequality (various samples)



Notes: Gini coefficients are calculated separately for the full sample, which includes East and West German workers, the West German sample, and the East German sample. Panels (a) and (b) are based on real hourly wages weighted with the corresponding cross-sectional weights. Solid lines represent the trend component of the applied Hodrick-Prescott filter (Hodrick and Prescott, 1997). Since annual data are applied, the smoothing parameter is $\lambda = 6.25$ according to the rule-of-thumb in Ravn and Uhlig (2002).

since 2000. This pattern of the overall wage mobility indicates that the between-region wage inequality converges over time. The decomposition of the overall mean logarithmic deviation by the two regions shows that between-region and within-region inequality contributed 30 and 70 percent, respectively, to the overall wage inequality in 1991.[10] In turn, the contribution of the between-inequality gradually diminished and has had a value of around 4.5 percent since 2000. Since a between-region inequality of zero means that the average wages in both regions are the same, there is convergence between the two regions, at least in average wages, since 1991. Thus, the overall inequality is mainly driven by the within-region inequality.

Furthermore, in order to obtain a more detailed picture of the wage distribution, the common decile ratios are calculated for West Germany between 1984 and 2014 and indexed to 1984 (see Figure 2, panel (b)).[11] Whereas there are merely slight changes in the decile ratios until 1995, the indexed 9/1 and 5/1 decile ratios experiences a rapid growth after 1996 and the 9/5 decile ratio after 2000. Due to the persistent increase in unemployment since 1990, low economic growth and the recessions in 1992,1993, and 2003, several reforms were undertaken between 1996 and 2005 in order to increase the flexibility of the labor market and reduce unemployment. Furthermore, unions have lost bargaining power since the mid 1990s due to a sharp decrease in amount of members and the decline in the share of workers covered by any kind of union agreement. This political and economic process

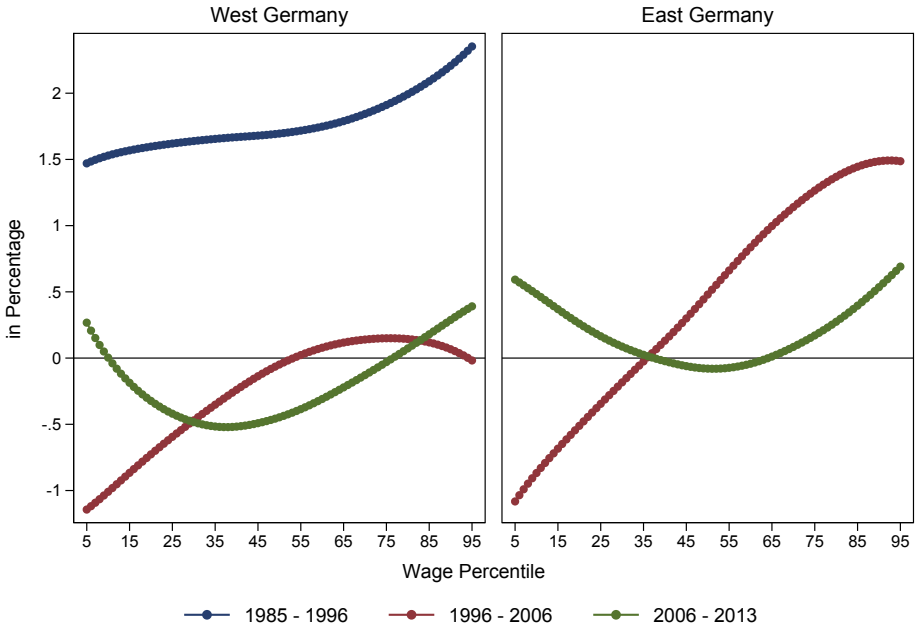
[10] The full results of the decomposition by the regions based on the mean logarithmic deviation are given in Table 7 in the Appendix. Since a decomposition based on the Theil index produced very similar results, they are not reported.

[11] The development of the decile ratios in East Germany are similar, though, the growth rates are greater (see Figure 15 in the Appendix).

supported and partly promoted the establishment and the expansion of a low-wage sector in Germany (Dustmann et al., 2014). Therefore, the low-wage earners experience less wage growth compared to the middle-wage and the high-wage earners. However, the increase of the 9/5 decile ratio since 2002 shows that the middle-wage earners experience less wage growth compared to the high-wage earners. This trend has strengthened since 2008 and shows a similar pattern to the 9/1 decile ratio. Interestingly, the development of the 5/1 decile ratio reverses precisely at this point in time and there has even been a decline in the ratio since 2008. Thus, two general conclusions can be drawn. First, the wage gap between low-wage as well as middle-wage earners to high-wage earners has increased rapidly since 2000. Second, the wage gap between low-wage and middle-wage earners has declined since 2008 and is currently even smaller than the gap between the middle-wage and high-wage earners.

Based on these results, a natural follow-up question arises: Is wage inequality more pronounced in certain parts of the wage distribution and how has it changed over time? This question can be answered, at least in a descriptive manner, by investigating the annual wage growth among the percentiles of the wage distribution in the base year (see Figure 3). Utilizing the development of the wage decile ratio 5/1 over time, the observation period is

Figure 3: Annual real hourly wage growth in West and East Germany



Notes: The data are pooled using three-year moving averages (i.e. the year 1996 includes data from 1995, 1996, and 1997) in order to prevent distortions in wage percentiles caused by outliers in a given year. Using locally weighted smoothing regressions (bandwidth 0.8 with 100 observations), both panels represent the annual change in logarithmic wages by the wage percentile in the base year.The wage distribution in both panels is based on the ranking of real hourly wages weighted by cross-sectional sample weights.

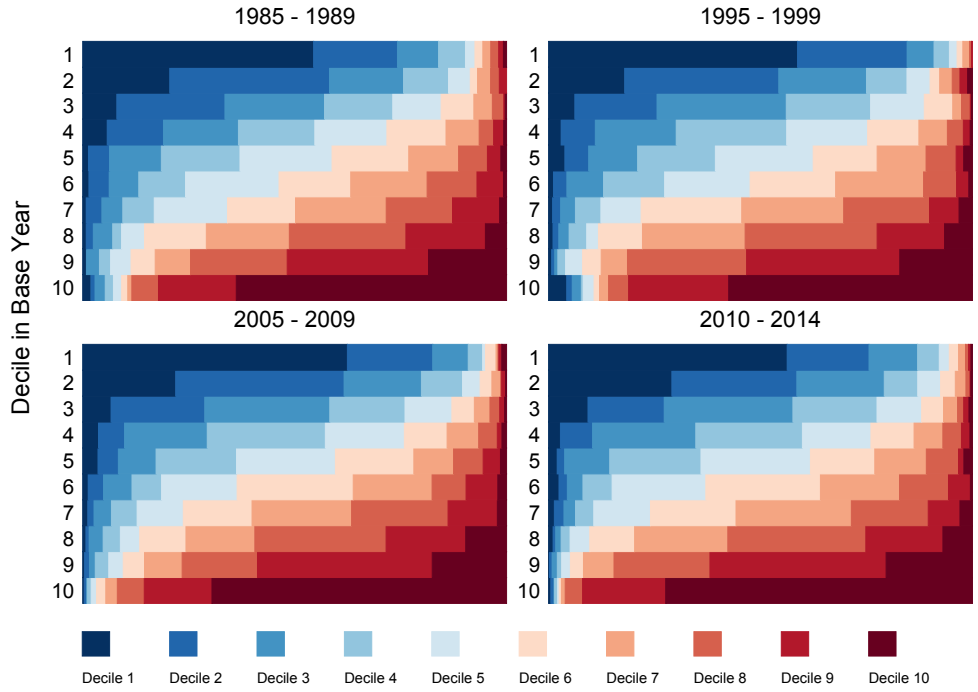
divided into three non-equal-sized time periods. Since there is no data available for East Germany in the 1980s, wage growth between 1985 and 1996 is restricted to West German workers. In this period, the slight increase in the decile ratios 9/1 and 9/5 as well as the

relatively constant trend of the decile ratio 5/1 are reflected in wage growth. The increase in wages between the 20th and 60th percentile is between 1.6 and 1.75 percent, whereas wage growth is slightly lower at the lower bound and somewhat higher at the upper bound. Thus, the rise in wage inequality in the 1980s and mid 1990s is due to a stronger wage growth at the top of the wage distribution (Dustmann et al., 2009). However, there is a monotonic function of wage growth over the wage distribution between the mid 1990s and mid 2000s. In West Germany (East Germany), wage losses occur up to the 54th percentile (35th percentile), whereas workers at the top experience slight wage increases. In particular, the large slope of East German wage growth along the wage distribution explains the rise of overall wage inequality in part during this period. Interestingly, in the aftermath of the Hartz reforms, there is a wage polarization along the wage distribution in West and East Germany. This result brings the nuanced version of the skill bias technical change hypothesis or polarization hypothesis according to Autor et al. (2003, 2006, 2008) back to wage structure debate in Germany. In previous studies, no wage polarization has been identified for the German wage growth either in the 1990s or in the early 2000s (Dustmann et al., 2009; Antonczyk et al., 2009). Since current research re-evaluates the polarization hypothesis for the 2000s and 2010s in the United States (Green and Sand, 2015; Beaudry et al., 2016) and in Germany (Pikos and Thomsen, 2015), the Subsection 4.2 focuses on two particular questions. To what extent is the observed wage polarization along the wage distribution attributable to the polarization hypothesis? Is the wage polarization and the performance of different tasks reflected in a worker's wage mobility?

3.2 Wage Mobility

The growth of wage inequality between the mid 1980s and mid 2000s implies that the wage gaps between the percentiles of the wage distribution have increased over time. This trend has been slowing down slightly in West and East Germany since 2006 due to less wage growth in the middle of the wage distribution relative to the lower and upper end. However, higher wage growth or less wage losses of particular wage percentiles do not ensure that workers in these percentiles experience an improvement in their relative wage position. On the one hand, workers' movement along the wage distribution depends on their own wage growth. On the other hand, the wage growth along the entire wage distribution determines whether a worker's own wage growth is sufficient to rise in ranks. Thus, the paradox case of a worker's downward mobility despite his or her own wage growth can occur if workers with a lower wage in the base year experience a much stronger wage growth and pass him or her in ranks. In general, wage mobility can be defined and illustrated in different ways, depending on the aim of the research. A commonly used illustration to show wage mobility in ranks is the descriptive transition matrix which measures the probability to move from a particular wage quantile, such as quintile, decile, or percentile, in the base year t to a certain quantile in the reporting year $t+s$. In Germany, workers in the lowest and in the top wage decile show a very high persistence in their wage ranks (see Figure 4). The probability

Figure 4: Descriptive transition probabilities between base and reporting year



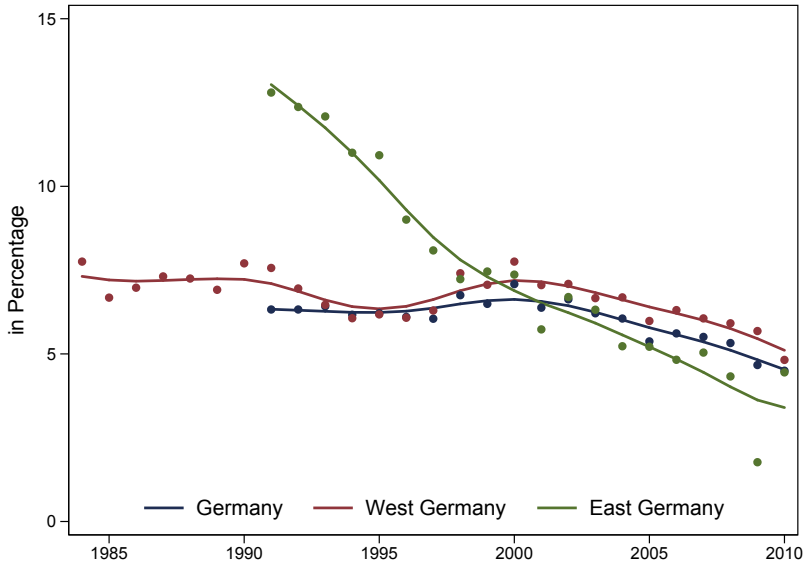
Notes: The data are pooled using three-year moving averages (i.e. the year 1996 includes data from 1995, 1996, and 1997) in order to prevent distortions in wage percentiles caused by outliers in a given year. Using locally weighted smoothing regressions, both panels represent the annual wage growth by the skill percentile in the base year. The wage distribution in both panels is based on the ranking of real hourly wages weighted by cross-sectional sample weights.

of staying in these wage deciles even after four years is between 54 and 72 percent over the observation period, whereby the probabilities of workers in the top decile are higher. Considering the wage mobility of workers who are in the lower (upper) three deciles in the base year, their probability of receiving a wage above (below) the median wage after four years are merely between 2 and 15.4 percent. This indicates that the likelihood of workers' downward or upward movement in deciles diminishes rapidly with increasing or decreasing wage deciles. In total, a decrease in upward mobility of low-wage earners and downward mobility of high-wage earners can be detected since the mid 1990s. Whilst transition matrices measure the transition probabilities between base year and reporting year deciles, they neglect three notable issues. First, a worker's downward or upward mobility within a decile is not taken into account in the calculation of transition probabilities. Second, overall wage growth along the entire wage distribution leaves the probabilities unchanged if the initial ranking of workers does not not change. Third, transition matrices do not directly consider the development of wage mobility over time.

The latter points to the issue that there is no generally accepted and unambiguous definition of intragenerational mobility in the empirical literature. In his pioneering work, Shorrocks (1978) defines mobility as the circumstance that reduces long-term inequality as it smoothes the individual wage or income fluctuations over time. Based on this idea, the Shorrocks mobility index is defined as the difference between the average of cross-sectional wage inequality and long-term wage inequality, which is the inequality of average individual

wages over time. Thus, the index measures to what extent wage mobility reduces average cross-sectional wage inequality and can be interpreted as an *equalizer index*. Applying a moving fixed time window of 4 years over the observation period shows that wage mobility is relatively constant in West Germany, with values of around 6.5 percent between 1984 and 2000 (see Figure 5). However, since 2000, wage mobility has gradually decreased, indicating

Figure 5: Shorrocks Mobility Index as an equalizer of long-term wages



Notes: Shorrocks Mobility Index is calculated separately for the full sample, which includes East and West German workers, the West German sample, and the East German sample, by applying 4-year time periods. Thus, for example, the point estimates for 1984 yield the wage mobility between 1984 and 1988. Estimates are based on real hourly wages weighted with the corresponding cross-sectional weights. Solid lines represent the trend component of the applied Hodrick-Prescott filter (Hodrick and Prescott, 1997). Since annual data are applied, the smoothing parameter is $\lambda = 6.25$, according to the rule-of-thumb in Ravn and Uhlig (2002).

that wage mobility reduced the long-term wage mobility by merely 4.8 percent in 2010. The same pattern is detected for the development of overall wage mobility. East Germany started with very high values of wage mobility in 1991, but experienced a sharp decline in the ongoing years. Since 2000, wage mobility in East Germany has even been significantly lower than in West Germany. Currently, merely 3.4 percent of the long-term wage inequality can be reduced through wage mobility in East Germany. Since the Shorrocks mobility index is nondirectional and scale invariant, i.e. merely relative income changes matter in the calculation, state dependence in wage ranks strongly increased after 2000 in West and East Germany. Therefore, a worker's probability to move in ranks along the wage distribution diminished over time.

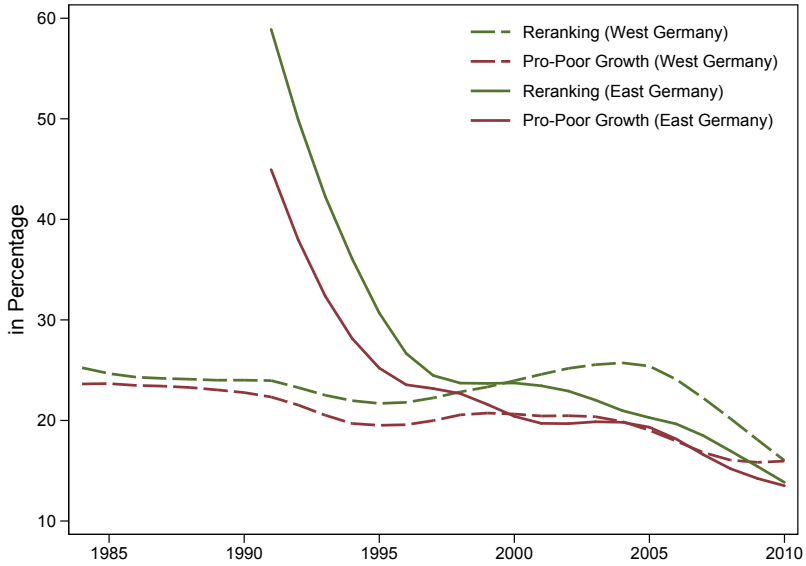
The Shorrocks Mobility Index depicts the change in relative incomes and the movements of individuals along the wage distribution in ranks. However, an individual's movements depend on his or her wage growth and on wage distance between two or more adjacent ranks. The latter implies that the extent of wage inequality is mechanically related to the extent of particular wage mobility measures. Jenkins and Van Kerm (2006) offer a method to analyze wage growth and changes in wage ranks between the base and the reporting year

simultaneously. Furthermore, they show that the change in the Gini coefficients between two points in time can be decomposed into a pro-poor growth and a reranking or mobility component. The former measures to what extent the changes in wages or wage growth in general benefits the low-wage earner more strongly than high-wage earners of the base year or vice versa. The latter measures the magnitude of individuals' movement along the wage distribution between the base and the reporting year. Applying the conventional Gini coefficient G in order to measure changes in wage inequality, the decomposition can be expressed by:

$$\Delta G = G_{t+s} - G_t = R - P \tag{2}$$

where R and P are the reranking and progressivity component, respectively, whereby the latter reduces wage inequality, unless the former overcompensates for it. In West Germany, wage mobility as well as the progressivity of wage growth decrease slightly between 1984 and 1996 from 25.2 and 23.6 percent to 22.2 and 20 percent, where both components are measured relative to the Gini coefficient in the base year and reported in percentage (see Figure 6). Since the reranking index is a relative-wages-weighted average of changes in

Figure 6: Decomposition of Gini coefficient changes in wages between base and reporting year



Notes: Decompositions are calculated separately for the West German and the East German sample applying 4-year time periods. Reranking and pro-poor growth index are given in percentage of the base year wage inequality, whereby the calculation of the conventional Gini coefficients is based on real hourly wages weighted with the cross-sectional weights of the base year. Solid lines represent the trend component of the applied Hodrick-Prescott filter (Hodrick and Prescott, 1997). Since annual data are applied, the smoothing parameter is $\lambda = 6.25$, according to the rule-of-thumb in Ravn and Uhlig (2002).

the social weights of individuals between the base and the reporting year, a value of 20 percent implies that wage inequality in the reporting year would have been 20 percent higher (relative to the base year) if wage growth had been equi-proportionate $P = 0$, i.e. each worker's wage increased by the same percentage. Furthermore, the progressivity component takes consistently positive values in East and West Germany over time, which indicates

that observed wage growth reduces wage inequality and is pro-poor, i.e. wage growth is concentrated more among the low-wage earner than the high-wage earner. This index yields the decrease in cross-sectional wage inequality in percentage of the base year value if there had been no reranking $R = 0$, i.e. the rank order of workers does not change between the base and the reporting year. Whereas the difference in the reranking and the progressivity component are relatively constant in East Germany, the two components start to diverge in West Germany between 2000 and 2005. The fairly constant progressivity combined with increasing mobility indicates that the growth in wage inequality between 2000 and 2009 is mainly driven by wage mobility. However, it is to an extent counterintuitive that wage inequality increase despite pro-poor growth in both regions due to the overcompensating effect of reranking. Since the decomposition method is based on tracking individuals' wage position over time, low-wage earners in the initial year might move towards middle-wage jobs in the reporting year due to pro-poor growth, but they are simultaneously replaced by new low-wage earners who were middle- or high-wage earners in the base year. If the new set of low-wage earners in the reporting year have, on average, a lower wage than the previous set of low-wage earners in the base year, the reranking index will exhibit the pro-poor growth index, which leads to an increase in cross-sectional wage inequality. Therefore, the decomposition method measures wage changes of a fixed wage group, whose membership is defined by the base year (progressivity) and adds a term that accounts for membership changes (reranking). As the 9/5 decile ratio has increased more strongly since 2000, after a rather flat phase before, and there was no considerable change in the growth pattern of the other decile ratios, the increase in wage inequality might be due to a higher reranking in the middle of the wage distribution. This is all the more likely because the conventional Gini coefficient is more sensitive to changes in the middle of the distribution.

4 Empirical Results

The empirical analysis evaluates the influence of individual characteristics, job stability variables, and employment characteristics on a worker's wage mobility in Germany. For this purpose, rolling 4-year time periods between 1993 and 2010 are used. Due to the reunification effects, the first two time periods after the reunification are not considered within the estimations in order to avoid distortions. Although the presentation of the estimation results is limited to three selected 4-year time periods, the conclusions are drawn taking the whole observation period into account.[12] Hence, a worker's age has a negative impact on his or her wage mobility, i.e. older workers show, on average, a lower wage mobility (see Table 1). The magnitude of this effect is relatively constant over time and ranges between 0.1 and 0.2 percentiles per year over the entire observation period. In contrast, a worker's job tenure in the base year has no significant impact on his or her wage mobility in two out of three presented time periods. Although job tenure did not have a significant impact in the

[12] The estimation results of the remaining time periods are available upon request.

Table 1: Determinants of wage mobility in different 4-year time periods (full sample)

	1995-1999		2005-2009		2010-2014	
Individual Characteristics						
Age	-0.122	(0.039)***	-0.115	(0.038)***	-0.146	(0.034)***
Female	-5.340	(0.831)***	-4.296	(0.655)***	-3.993	(0.608)***
Migration Background	-1.285	(0.778)*	-0.677	(0.710)	-0.873	(0.620)
Low-Skilled			*reference*			
Medium-Skilled	2.172	(1.004)**	2.571	(1.003)**	3.112	(1.010)***
High-Skilled	7.867	(1.455)***	7.385	(1.276)***	8.153	(1.227)***
Job Stability						
At Least 1 Job Change	-1.075	(0.861)	-0.712	(0.788)	0.617	(0.649)
Unemployment Experience	-4.085	(1.359)***	-5.269	(1.656)***	-6.217	(1.348)***
Job Tenure	0.052	(0.040)	0.035	(0.036)	0.068	(0.032)**
Employed Part-Time	-3.144	(1.075)***	-2.774	(0.788)***	-1.633	(0.685)**
Employment Characteristics						
Firm Size: < 20			*reference*			
Firm Size: 20-200	1.584	(0.867)*	2.413	(0.743)***	1.643	(0.686)**
Firm Size: 200-2000	4.649	(0.918)***	4.880	(0.839)***	3.960	(0.747)***
Firm Size: > 2000	6.778	(0.955)***	6.655	(0.860)***	5.863	(0.763)***
Manufacturing			*reference*			
Agriculture	-7.699	(2.552)***	-7.203	(2.399)***	-2.175	(2.485)
Energy	4.345	(2.803)	-0.943	(2.492)	-2.380	(2.258)
Mining	-0.613	(3.560)	1.608	(4.441)	12.431	(4.979)**
Construction	-0.631	(0.861)	-0.533	(0.828)	-0.445	(0.743)
Trade	-2.274	(1.150)**	-5.998	(0.946)***	-5.534	(0.877)***
Transport	-2.286	(1.394)	-2.623	(1.303)**	-2.463	(1.126)**
Bank,Insurance	2.513	(1.473)*	2.914	(1.203)**	0.235	(1.186)
Services	0.133	(0.887)	-2.458	(0.741)***	-2.513	(0.706)***
Legislators/Senior Officials/Managers			*reference*			
Professionals	3.904	(1.873)**	-0.263	(1.180)	1.197	(1.099)
Technicians/Associate Professionals	-2.324	(1.730)	-4.830	(1.177)***	-2.733	(1.094)**
Clerks	-3.256	(1.819)*	-8.324	(1.322)***	-6.208	(1.235)***
Service Workers/Shop and Market Sales Workers	-7.909	(2.122)***	-11.436	(1.444)***	-7.729	(1.430)***
Skilled Agricultural/Fishery Workers	-7.927	(3.210)**	-13.083	(3.421)***	-12.766	(2.509)***
Craft and Related Trades Workers	-7.976	(1.814)***	-11.223	(1.364)***	-9.535	(1.263)***
Plant and Machine Operators and Assemblers	-8.855	(1.873)***	-13.713	(1.485)***	-10.980	(1.401)***
Elementary Occupations	-11.546	(2.100)***	-13.300	(1.606)***	-10.023	(1.542)***
Change of Occupation	0.011	(0.647)	-0.512	(0.553)	0.268	(0.511)
Change of Industry	0.463	(0.711)	0.173	(0.631)	-0.648	(0.590)
East Germany	-10.704	(0.969)***	-6.224	(0.690)***	-6.012	(0.612)***
R^2	0.269		0.234		0.230	
Obs.	3323		4096		4571	

Notes: Estimations are based on the full sample, which indcludes East and West German workers. Wage mobility is calculated using cross-sectional weights. Classification of industries is based on ISIC Rev. 3 and classification of occupations is based on ISCO88. Workers' initial wage percentiles or ranks are included, but not reported. Robust standard errors are in parentheses. ***significant at 1 percent, **significant at 5 percent, *significant at 10 percent.

1990s, there has been a significant positive association between job tenure and wage mobility since 1999. The results for the 1990s can be due to a higher correlation between a worker's age and his or her job tenure, which might lead to insignificant coefficients of one of the two covariates.[13] Since the estimations control for plenty of socio-economic characteristics, a worker's migration background does not cause significant differences in wage mobility.[14] Furthermore, a job change within the 4-year time periods has no significant influence on a worker's wage mobility. On the one hand, workers who have better alternatives might change

their workplace to achieve higher wages. On the other hand, workers might involuntarily switch to low-wage employment due to family reasons or imminent unemployment. Thus, the lack of job change effect could be due to these two mutually compensating causes. Moreover, a worker's unemployment experience within the time period has a highly significant negative impact on his or her wage mobility. An additional month of unemployment between 2010 and 2014 lowers an employee's wage mobility by 0.5 percentiles. Across the presented time periods, there is an increase in the importance of unemployment spells for wage mobility. Since the considered base years are respectively in economic upturns, the three time periods start in comparable points of the business cycle.[15]

Additionally, wage mobility increases with firm size.[16] Employees who work in firms with more than 2000 employees show a wage mobility of almost 6 percentiles higher than similar employees who work in firms with less than 20 employees. There are several causes for such an positive association between firm size and wage mobility or wages, in general.[17] First, larger firms show a more unionized workforce that can bargain for higher wages than comparable workers in smaller firms. Second, the capital to labor ratio is higher in larger firms. Thus, a worker's productivity and wage is higher in larger firms. Furthermore, large firms tend to adopt new technologies and process innovations more quickly than small firms, which increases workers' productivity (Idson and Oi, 1999). Third, larger firms are more likely to fill their vacancies internally than externally. Thus, workers could receive higher wages due to changing their position within the firm. Additionally, this reduces a firm's searching and hiring costs (Gerlach and Schmidt, 1989). Fourth, firms with many employees are more likely to have a higher survival rate and invest more in training their workers (Brown and Medoff, 2003). Moreover, the firm size wage premium can be driven to some extent by the self-selection of less able workers into small, unstable, and low-paying firms (Winter-Ebmer, 1995).

Taking a closer look at the effect of a worker's occupation on his or her wage mobility shows declining coefficients with descending categories, since managers are the reference category. This is due to the classification scheme of the occupations that is based on an occupation's skill requirements and the degree of specialization. Thus, the occupation variable covers the specific part of a worker's human capital, whereas the educational attainment measures his or her general human capital. Therefore, workers in elementary occupation and plant or machine operators have around a 10 percent lower wage mobility than managers. In particular, professionals and clerks suffered a loss in their wage mobility compared to

[13] Neither age nor job tenure show a significant quadratic effect on the workers' wage mobility. Thus, there is no curvilinear relationship for both covariates.

[14] In the estimations, workers with a migration background and workers with migration experience are combined. People with migration experience are foreign-born persons, whereas people with migration background are born in Germany and have parents or grandparents who are foreign-born.

[15] The previous recessions were in the following periods: January 1991 - April 1994, January 2001 - August 2003, and April 2008 - January 2009.

[16] The positive association between wages and the firm size was first discovered by Moore (1911) who investigated the daily wages of Italian women in textile mills.

[17] See Brown and Medoff (1989), Abowd et al. (1999), and Oi and Idson (1999) for a review of the literature on the firm size wage premium.

professionals. Whereas professionals show a 3.8 percentiles higher wage mobility than managers in 1993, the wage mobility difference between both occupations has not been significantly different from zero since the beginning of the 2000s. Furthermore, clerks' estimation coefficient decreased from -1.6 in 1993 to -6.2 in 2010.

Additionally, a worker's industry affiliation partly affects his or her wage mobility. In particular, workers in the trade industry have been significantly less mobile in terms of wage percentiles than workers in manufacturing since the beginning of the 2000s. Over time, the negative effect is relatively stable and ranges between 5 and 6 percentiles. The same applies for the transport industry. Although workers in the mining industry experience a significantly upward mobility in the last 4-year time period, this result is only an outlier. In previous years, there is no significant difference in the wage mobility of workers of the manufacturing and mining industry.

Whereas workers in the service industry did not significantly differ in their wage mobility from workers of the manufacturing industry until 1999, their wage mobility slightly decreased several years after 2000. As the service industry includes various sub-industries, which can be different in their qualification and employment structure, the estimations are repeated using a more detailed industry definition (see Table 2).[18] Applying the NACE Rev.

Table 2: Effect of detailed industry categories on the wage mobility in different 4-year time periods (full sample)

	1995-1999		2005-2009		2010-2014	
Manufacturing			*reference*			
Agriculture/Fishing/Mining	-5.674	(2.140)***	-3.873	(2.318)*	-0.542	(2.362)
Electricity/Gas/Water	3.948	(2.771)	-0.735	(2.479)	-2.493	(2.245)
Construction	-2.150	(1.075)**	-0.624	(1.240)	-3.468	(1.012)***
Wholesale And Retail Trade	-2.789	(1.179)**	-5.830	(0.935)***	-5.706	(0.873)***
Hotels And Restaurants	-3.815	(2.548)	-7.804	(1.882)***	-8.691	(1.824)***
Transport, Storage, and Communication	-2.698	(1.382)*	-2.512	(1.275)**	-2.745	(1.094)**
Financial Intermediation	2.053	(1.465)	3.048	(1.164)***	0.118	(1.148)
Real Estate, Renting, and Business Activities	2.871	(1.443)**	-1.456	(1.004)	-1.393	(0.872)
Public Administration/Social Security	-1.709	(1.280)	-1.373	(1.076)	-1.554	(0.992)
Education	0.090	(1.566)	-1.332	(1.407)	0.389	(1.226)
Health And Social Work	-2.201	(1.241)*	-3.874	(0.997)***	-4.674	(0.874)***
Other Industries	1.705	(1.852)	-2.338	(1.484)	-3.452	(1.322)***

Notes: Estimations are based on the full sample, which includes East and West German workers. Wage mobility is calculated using cross-sectional weights. Classification of industries is based on NACE Rev. 1, where "agriculture", "fishing", and "mining" are combined into a category and "other community activities", "private households", and "extra-territorial organization" are combined into "other industries". The classification of occupations is based on ISCO88. Workers' initial wage percentiles or ranks are included, but not reported. Robust standard errors are in parentheses. ***significant at 1 percent, **significant at 5 percent, *significant at 10 percent.

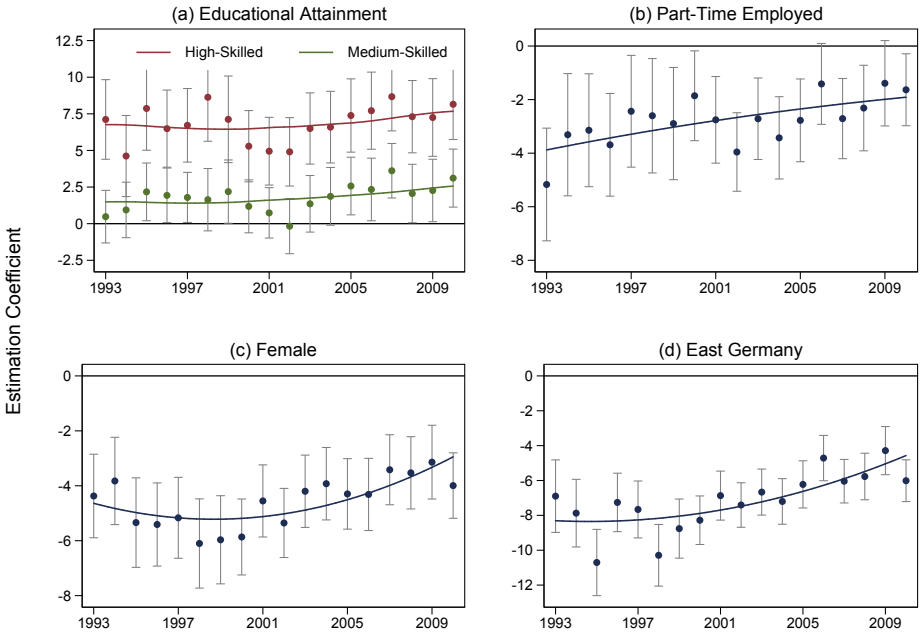
1 level 1 industry categories enables the detailed breakdown of the service sector, whereby some industries, such as agriculture, fishing, and mining, are grouped together due to a small number of valid observations in the corresponding cells. Workers of the "wholesale and retail trade" and "hotels and restaurants" industry which were aggregated to the previous "trade" industry show significantly less wage mobility than workers in manufacturing. With respect to the sub-industries of the service sector, the results show that the negative effect for the service sector is driven by the sub-industry "health and social work". Here, workers'

[18] Full estimation results are in Table 8 in the Appendix.

wage mobility declines relative to workers in the manufacturing industry over time. Their difference in wage mobility to workers in manufacturing increased from 2 percentiles in 1993 to 4.6 percentiles in 2010. The workers of the other sub-industries of the service sector do not show a significant difference in their wage mobility to workers in manufacturing. This has especially applied since the 2000s. Ultimately, neither a worker's change in occupation nor change in industry within the time periods have a significant influence on his or her wage mobility. Here, the same reasons apply as for a worker's job change.

Some covariates show a clear trend in the extent of their effect on a worker's wage mobility over the entire observation period (see Figure 7). Hence, women have a lower wage

Figure 7: Development of selected estimation coefficients over time (full sample)



Notes: Solid lines are local polynomial smooth functions of degree 3, whereas spikes and cap lines represent the 95 percent confidence limits of estimation coefficients. Estimations are based on the full sample, which includes East and West German workers. Wage mobility is calculated using cross-sectional weights.

mobility than men over time. Whereas at the beginning of the 1990s, this difference slightly increased due to reunification effects, the effect of a worker's gender on the wage mobility has gradually declined since 1998. However, this convergence of women and men occurs relatively slowly. In 2010, women were still, on average, 4 percentiles less mobile in wage ranks than men. A similar trend can be detected for workers living in East Germany. There is a slow convergence between East and West German workers in their wage mobility. In particular, since 2001 the wage mobility gap between West and East Germany has gradually declined. However, the difference in wage mobility was still 6 percentiles in 2010. Thus, the labor market adjustments in East Germany occur very slowly with regard to wage mobility and wage development, although 25 years have already passed since reunification (Gernandt and Pfeiffer, 2008). In turn, the negative impact of part-time employment on a worker's wage mobility diminishes over time. In contrast to the trend of previous covariates, the

convergence between part-time and full-time workers' wage mobility is almost entirely completed at the end of the observation period. Between 1993 and 2010, the wage mobility gap decreased from 5.1 percentiles to 1.6 percentiles.

Taking a closer look at educational attainment's impact on a worker's wage mobility, wage mobility increases with increasing educational degree. In 2010, high-skilled workers and medium-skilled workers were more mobile than low-skilled workers by 8 and 3 percentiles, respectively. Over time, the extent of these effects has been relatively constant, however there has been a slightly rising trend in the estimation coefficients of both education categories since the beginning of the 2000s. At first glance, a relatively constant effect of educational attainment on workers' wage mobility might not coincide with the skill biased technical change hypothesis, which implies that industrialized countries, such as Germany, have experienced a rise in the relative demand for high-skilled employees since the 1980s or 1990s (Katz and Autor, 1999). The skill biased technical change is based on the introduction of computer technology in the workplace and the greater digitization of work. In turn, the workforce is affected differently by this development, since computer technology favors high-skilled jobs and disadvantages low-skilled jobs. Thus, the larger productivity increases of human capital relative to the productivity gains of the other production factors should result in larger increases in high-skilled wages relative to increases in low-skilled wages (Hornstein et al., 2005; Acemoglu and Autor, 2011). Whether the relative wages of high-skilled and low-skilled workers increase in the long run depends on the productivity effect and the relative labor supply. If the latter shifts towards high-skilled labor, it partly compensates for the productivity effect on relative wages (Acemoglu, 1998, 2002).[19] As wage inequality has strongly increased in Germany since the beginning of the 1990s, this development can be partly attributed to the skill biased technical change (Dustmann et al., 2009; Antonczyk et al., 2009). In turn, a higher wage inequality entails the expansion of the wage thresholds between the percentiles along the wage distribution. Since wage growth increases along the wage distribution due to skill biased technical change (Card et al., 2013), high-wage earners have to generate stronger wage increases than low-wage earners in order to ascend along the wage distribution. As high-skilled workers tend to be at the upper end and low-skilled workers at the lower end of the wage distribution, a constant estimation coefficient across the educational categories over time implies a stable influence on wage mobility, though the effect of education on a worker's wage growth has to be increased.

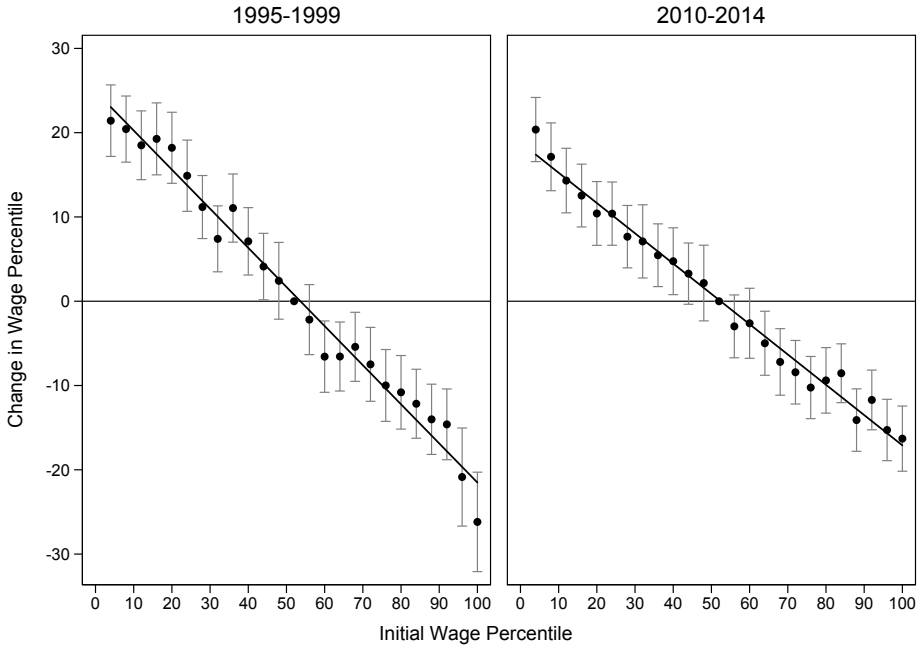
4.1 State Dependence in Wage Mobility

In addition to the socio-economic and demographic characteristics, a worker's wage mobility depends on his or her initial wage percentile in the base year. Workers who are at the lower end of the wage distribution experience an upward mobility relative to median workers,

[19] In his pioneering work, Tinbergen (1974) had already suggested that the technological trend will increase the demand for more skilled labor and characterized the development of the wage structures as a "race between demand for third-level manpower due to technological development and supply of it due to increased schooling".

whereas workers who are at the upper end of the wage distribution show a downward mobility relative to median workers (see Figure 8). This relationship applies to all employed

Figure 8: Change in wage percentiles due to a worker's initial wage percentile (full sample)



Notes: Estimations are based on the full sample, which includes East and West German workers. Solid lines are linear fits, whereas spikes and cap lines represent the 95 percent confidence limits of the estimation coefficients. Wage mobility is calculated using cross-sectional weights. The reference point is a worker who is between the 48th and 52nd percentile of the wage distribution in the base year.

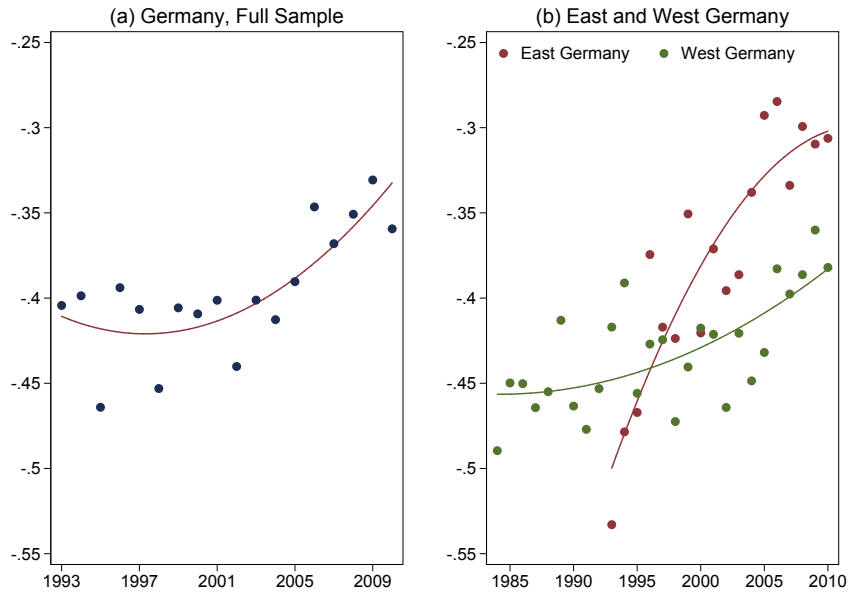
4-year time periods. In relation to the median worker, a worker who started in the bottom four percentiles in 1995 moved, on average, by 21.2 percentiles upward, whereas a worker starting in the top four percentiles moved, on average, 26.2 percentiles downwards. Thus, there were several rank changes between workers at both ends of the wage distribution as well as in middle of the wage distribution. However, workers' wage mobility depending on their initial rank changed in 2010. Although the impact of the initial percentile at the lower end of the wage distribution is only slightly smaller, workers from above-median percentiles show significantly less downward mobility. A worker starting in the top four percentiles experiences merely a downward mobility of 16 percentiles relative to the median worker. Thus, high-wage earners show less downward mobility or have a lower probability to move downwards along the wage distribution. Therefore, the closer the estimation coefficients of the initial wage percentiles are to the zero value, the smaller is the impact of a worker's initial wage percentile on his or her wage mobility. This relationship can be graphically represented by linear fit over the estimation coefficients of the particular initial ranks. Thus, two polar cases can be distinguished from the slope of the linear fit. First, if the linear fit is equal to the bisector, workers at the bottom of the wage distribution swap their position with workers at the top of the wage distribution. The top wage-earner becomes the bottom wage-earner after four years and vice versa. Second, the slope of the linear fit is equal to zero. Thus, the initial wage percentiles have no significant impact on a worker's wage mobility after controlling for

the basic set of covariates. Both high-wage and low-wage earners remain in the same wage rank after four years. Since no worker moves depending on his or her initial wage percentile, this can be interpreted as an extreme form of state dependence.

State dependence, in general, occurs if a person's economic status exhibits substantial serial persistence over time and transitions between different economic status are lowered. [20] In general, there are two explanations for serial dependence (Heckman, 1981). On the one hand, persistence might be the result of "true dependence", i.e. the current position of a person directly affects his opportunities or preferences to take another position. On the other hand, the persistence might occur due to genuine state dependence, i.e. there is observed or unobserved individual heterogeneity that drives the observed persistence. However, the extent of genuine state dependence can be considerably reduced if observable individual characteristics and selection into the observed position is accounted for (Stewart and Swaffield, 1999; Cappellari, 2007). Since plenty of socio-economic and demographic covariates are used within the estimations, the slope of the linear fit should reflect true state dependence to a major extent. Furthermore, a greater absolute slope implies less aggregate state dependence in workers' wage mobility. Over the observation period, the aggregate state dependence generally increased in the full sample, which includes East and West German workers. Between 1993 and 2004, state dependence was relatively constant around the value -0.4, except for the outliers in 1995, 1998, and 2002 (see Figure 9). However, since 2005, the impact of a worker's initial wage percentile on his or her wage mobility has gradually declined and state dependence reached a value of -0.36 in 2010. A similar trend can be detected separately for West German workers. There, between 1984 and 2004, the state dependence does not take any value below -0.5 or above -0.4. Thus, there is no clear trend initially apparent. However, since 2005, the -0.4 mark has been continuously surpassed and the aggregate state dependence amounted to -0.38 in 2010. A rise in workers' persistence probability in their initial wage percentile can also be ascertained for East German workers. In the first years after reunification, state dependence in East Germany was even lower than in West Germany, which can be attributed to reunification effects and has already been mirrored in a higher aggregate wage mobility in East Germany during that time. However, since 1996, the state dependence of wage mobility has been higher in East Germany than in West Germany. In particular, since 2005, East German values have been around the -0.3 mark. Although the average difference in the wage mobility of East and West German workers has declined since 2001 due to the estimation results, an East German worker's probability of persistence in his or her initial wage percentile is higher. This indicates that workers' wage mobility along the whole wage distribution is lower in East Germany than in West Germany. Workers at the lower end of the wage distribution move upwards by less percentiles, whereas workers at the upper end of the wage distribution move downwards by less percentiles.

[20] State dependence is investigated in studies about a person's transition probability from welfare receipt to no welfare receipt (Jenkins and Cappelari, 2014; Königs, 2014), from unemployment to employment (Wunder and Riphahn, 2014), and from low-wage employment to high-wage employment (Mosthaf et al., 2011; Aretz and Gürtzgen, 2012).

Figure 9: Development of aggregated state dependence over time



Notes: Estimations based on the full sample includes East and West German workers and a region dummy for East Germany. Estimation based on West or East German Samples include federal state dummies. West German Samples additionally includes a dummy for whether workers migrated from East to West Germany. Wage mobility is based on 4-year time periods and calculated using cross-sectional weights. The reference point for estimation coefficients of the initial wage percentiles is a worker who is between the 48th and 52nd percentile of the wage distribution in the base year.

Ultimately, workers' probability of persistence in their initial wage percentiles increased overall, but more so in East Germany than in West Germany.

4.2 Tasks, Task Intensity, and Wage Mobility

The skill biased technical change predicts that wages have increased monotonously over employees' educational degree since the introduction of computer technology at workplaces. Therefore, low-skilled workers' jobs can be replaced more easily by new technologies and experience wage losses or lower wage growth over time, whereas high-skilled jobs are complemented and extended, which leads to higher wages or greater wage growth. However, Autor et al. (2003) point out that the substitution process does not address the general level of education, but rather draws on specific work activities. By aggregating the work activities of different occupations to tasks, they show that the diffusion of the computer technology in the production process induced a substitution of routine cognitive and routine manual tasks which follow explicit rules and a complementation of non-routine problem-solving and complex communications tasks. Furthermore, Autor et al. (2006, 2008) discover that low-skilled workers' wages and employment did not decline in the United States in the 1990s, but rather these changes occurred to middle-skilled workers. Additionally, they show that, in general, workers performing mainly routine jobs are located in the middle of the wage distribution, whereas workers performing mainly non-routine jobs are at the upper and lower end. Therefore, the nuanced version of the skill biased technical change

predicts a polarization of wages and employment along the wage distribution. In a follow-up paper, Autor and Dorn (2013) show that wage and employment polarization at the lower end of the skill distribution between 1980 and 2005 is mainly driven by service occupations in the United States. Since routine tasks were substituted through computerization, low-skilled workers re-allocated themselves into service occupations which require direct physical proximity and flexible interpersonal contact. Goos and Manning (2007) receive similar results with regard to the employment growth pattern, but different results for the wage growth in the United Kingdom between 1975 and 1999. Whereas workers at the lower end of the skill distribution show wage losses relative to workers at the middle, employment polarization explains one-third of the rise in the 5/1 wage decile ratio and one-half of the rise in the 9/5 wage decile ratio.

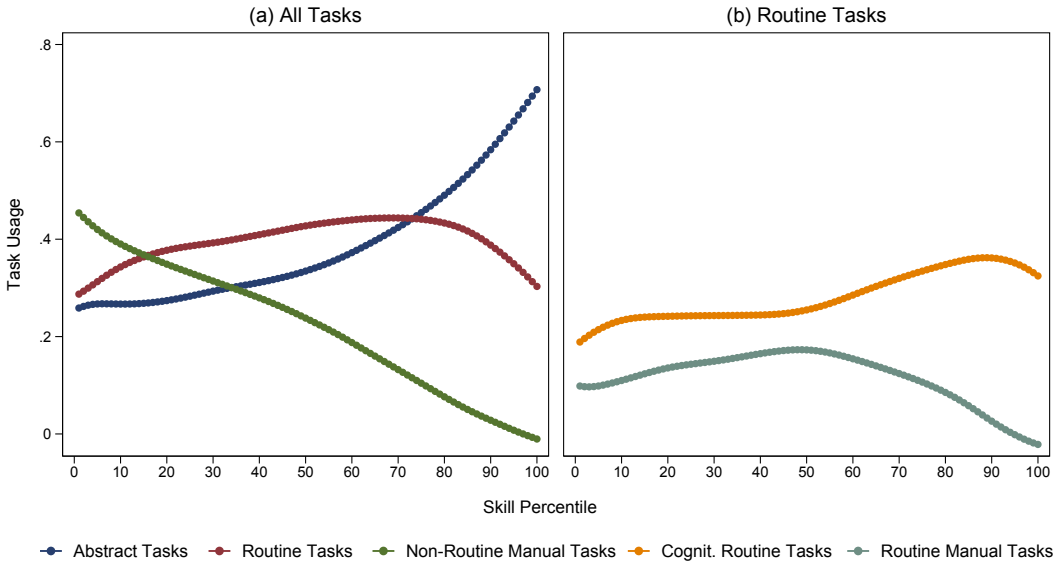
In Germany, Spitz-Oener (2006) examined the routinization hypothesis and detects an employment polarization irrespective of the educational degree between 1979 and 1999. The first skill decile (including mainly non-routine manual tasks) and the top three skill deciles (including mainly non-routine analytic and interactive tasks) experienced employment growth, whereas the second and third deciles (including mainly routine manual and cognitive tasks) evinced employment losses. Dustmann et al. (2009) confirm the employment polarization in the 1980s and 1990s. However, they find no evidence of a wage polarization in either of the two decades. Whereas average wages in skill percentiles above the median are positively correlated with employment changes, average wages in skill percentiles below the median are negatively correlated. Therefore, the increase in wage inequality in the early 1990s, especially at the lower end of the wage distribution, can be better explained by temporary events, such as de-unionization and supply shocks (reunification and stark inflow of low-skilled Eastern Europeans). Antonczyk et al. (2009) support these results and conclude that the task-approach can explain the wage growth at the upper end of the distribution, but not the wage changes at the lower end. Thus, the rise in wage inequality can only partly explained by the relative task demand shifts.

Recent studies question the wage polarization as a long-term phenomenon, claiming that wage polarization was limited to the labor market in the United States and is merely an exception rather than a rule (Green and Sand, 2015). Beaudry et al. (2016) detect that there has been no wage growth or slight wage growth for abstract tasks in the United States since 2000, whereas workers performing mainly routine and manual tasks have experienced no wage changes or slight declines in the their wages. In Germany, Pikos and Thomsen (2015) find an employment polarization from 1979 to 1999 and a substitution of routine tasks by non-routine tasks. However, the pattern is reversed from 1999 to 2012. There is considerable employment growth in routine tasks and losses in non-routine tasks, which is in line with the demand reversal results according to Beaudry et al. (2016). Thus, the extent to which the substitutability of routine tasks by the computer technology affects wage growth after the turn of the century can be questioned. Since wage growth of certain occupations

or workers determines their movements along the wage distribution, the impact of tasks carried out in the base year of the 3-year-time periods on a worker's wage mobility will be examined in more detail. For this purpose, a newly available measurement method for the operationalization of tasks based on the expert database BERUFENET of the German Federal Employment Agency is applied (Dengler et al., 2014). According to Autor et al. (2003, 2006, 2008) the technical change has a non-monotonic effect on the wage growth along the skill distribution due to the implementation of computer technology. The nuanced version of the skill biased technical change predicts that workers in manual non-routine and abstract occupations are more strongly represented at the lower and upper end of the skill or wage distribution, whereas employees performing mainly cognitive routine and manual routine occupations are mainly located in the middle. Since computer technology substitutes routine tasks and complements non-routine tasks, wage growth along the skill distribution should be polarized, i.e. the wage growth at both ends of the skill distribution is higher than in the middle. In order to test both assumptions of this simple demand-based explanation of the skill biased technical change, the distribution of task usage, and the polarized wage growth, the skill distribution is prepared following the calculation methods outlined in Goos and Manning (2007) and Autor and Dorn (2013). Data on the 3-digit KldB 2010 occupations are combined with information on workers' industry based on the NACE level 1 classification, whereby there are 259 occupation-industry categories in 2001.[21] These occupations are ranked according to their skill level and grouped into 100 equally-sized groups, where skill ranks are approximated by the average wage of workers in the occupations in 2001. Furthermore, each percentile of the skill distribution corresponds to percentiles of the overall employment, i.e. each skill percentile polls the same nominal amount of employment, measured in working hours. Ultimately, the task usage (task intensity) is calculated for each skill rank and the estimates of the locally weighted smoothing regressions are plotted over the skill distribution (see Figure 10). Taking a closer look at the task usage along the skill distribution shows that the share of workers performing abstract tasks increases strongly as of the 51st skill percentile from 33 percent to 71 percent, whereas the share is slowly rising from 25 percent to 33 percent between the lower end and the middle. Although the share of non-routine manual workers is monotonically decreasing over the skill distribution, the shares in the middle are still between 29 percent and 20 percent. Ultimately, the shares decrease rapidly as of the 50th percentile. In contrast to the routinization hypothesis, task usage of routine tasks increase gradually along the skill distribution up to the 70th percentile and decreases hereafter to its initial value in the lowest percentile. Breaking down the routine tasks into its two components reveals that cognitive routine tasks and manual routine tasks take an opposite development in task usage in the upper tail of the skill distribution. Routine manual occupations are, in general, more frequently located in the middle, but their employment shares are relatively small along the entire skill distribution. In contrast to the routinization hypothesis, cognitive routine task intensity increases from 25 percent in the

[21] For the sake of readability, the term "occupation" is used instead of "occupation-industry category" in the following explanations.

Figure 10: Task usage along skill distribution in 2001 (full sample)

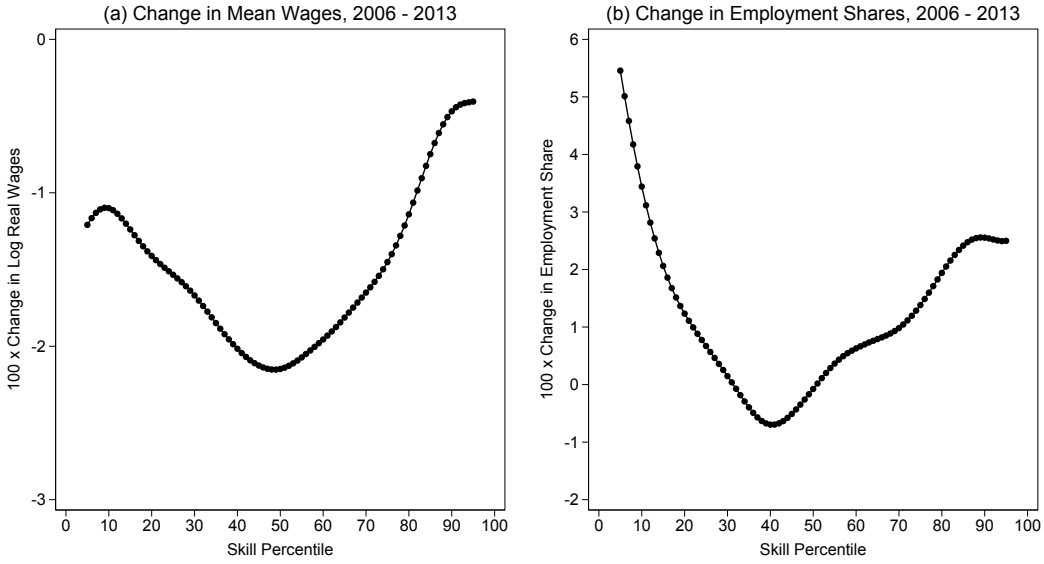


Notes: The data are pooled using three-year moving averages (i.e. the year 2001 includes data from 2000, 2001, and 2002) in order to prevent distortions in skill percentiles caused by outliers in a given year. Using locally weighted smoothing regressions (bandwidth 0.8 with 100 observations), the figure depicts the share of workers performing various task types by 2001 skill percentile. The skill distribution is based on the ranking of 3-digit KldB 2010 occupations combined with NACE level 1 industry information according to mean wages weighted by working hours times cross-sectional sample weights in 2001 and on the subsequently grouping into 100 equal-sized groups with regard to overall employment. Employed sample includes East and West German workers.

50th skill percentile up to 36 percent in the top skill rank. Moreover, their employment shares are relatively constant in the lower end and the middle (around 23 percent). Thus, the predicted distribution of tasks along the skill distribution can be confirmed for abstract tasks, manual non-routine tasks and, in general, routine tasks, but the distribution of cognitive tasks deviates strongly from the suggestions.

Since there was some descriptive evidence on the polarization of wage growth along the wage distribution as of 2006, the average wage growth and the change in employment shares in occupations along the skill distribution based on 2001 is examined (see Figure 11). The routinezation hypothesis predicts that the computerization of production processes triggers a polarization of wage growth and employment growth along the skill distribution. In general, all occupations experience, on average, wage losses between 2006 and 2013 along the skill distribution based on 2001. In contrast to the deviations of the distribution of tasks from the polarization hypothesis, the wage polarization is still maintained using the skill distribution instead of the wage distribution. The change in employment over the same period also shows a polarization along the skill distribution. This pattern can be partly explained by the routinezation hypotheses. There is a greater wage and employment growth at the upper end of the skill distribution due to the higher employment share of abstract tasks. The same might be true for the lower end of the skill distribution due to a higher share of non-routine manual tasks. Since routine tasks are the most common working activity in the middle of the skill distribution, the lower wage and employment growth might point to the substitution of routine tasks by automation. While this might be the case for manual

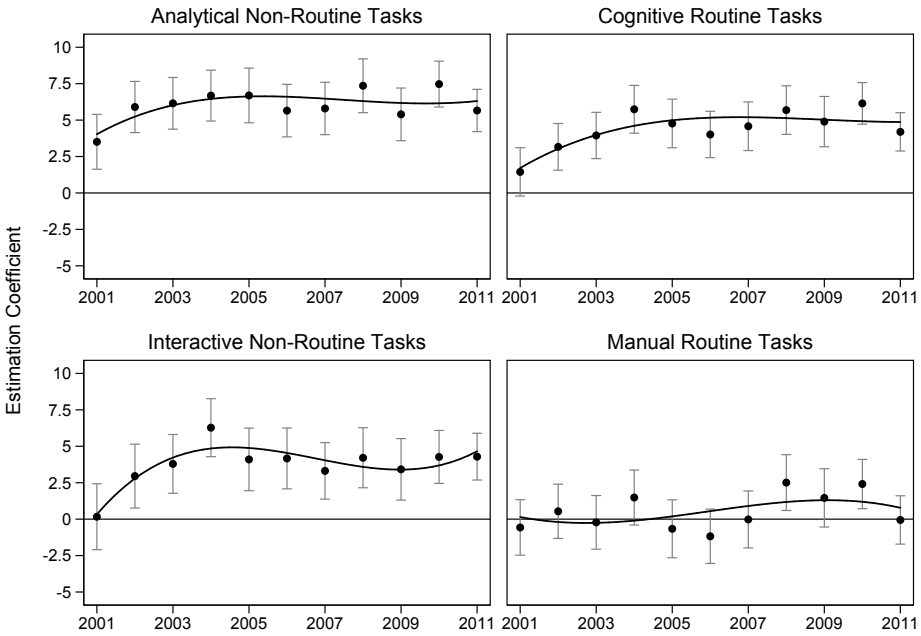
Figure 11: Annual wage growth and changes in employment shares along skill distribution (full sample)



Notes: The data are pooled using three-year moving averages (i.e. the year 2001 includes data from 2000, 2001, and 2002) in order to prevent distortions in skill percentiles caused by outliers in a given year. Using locally weighted smoothing regressions (bandwidth 0.8 with 100 observations), Panel (a) depicts the share of workers performing various task types by 2001 skill percentile and Panel (b) represents the 100 times change in logarithmic mean wages by 2001 skill percentile. The skill distribution in both panels is based on the ranking of 3-digit KldB 2010 occupations combined with NACE level 1 industry information according to mean wages weighted by working hours times cross-sectional sample weights in 2001 and on the subsequently grouping into 100 equal-sized groups with regard to overall employment. Employed samples include East and West German workers.

routine tasks, as they are more prevalent in the middle of the skill distribution, this statement can not be clearly made for cognitive routine tasks. In a recent work, Pikos and Thomsen (2015) ascertain two aspects of wage development in Germany between 1999 and 2012 that explain the observed wage and task usage pattern so far. First, for occupations which consist of cognitive tasks, they detect a rise in wages, which was slightly greater for routine cognitive tasks than for non-routine cognitive tasks. Second, occupations where routine manual tasks are performed experienced wage decreases, whereas slight wage increases were observed for occupations where non-routine manual tasks are performed. Therefore, the wage losses seen for occupations consisting of routine manual tasks might overcompensate the slight wage growth experienced by occupation where other tasks are mainly performed in the middle of the distribution. Putting the focus back on wage mobility, the evidence of wage changes across the occupations where various tasks are performed is reflected in the estimations (see Figure 12). As workers' wage growth directly affects their movement along the wage distribution, the main task type of occupations is additionally considered in the estimates for wage mobility. Since occupations which contain mainly manual non-routine work activities are the base category, estimated coefficients are interpreted in relation to this category. Both types of abstract tasks, analytical non-routine and interactive non-routine, continuously show a higher wage mobility. Over time, the estimates for analytical non-routine tasks have remained relatively constant at between 3.5 and 7.3 percentiles of increased wage mobility.

Figure 12: Development of tasks' impact on wage mobility over time (full sample)

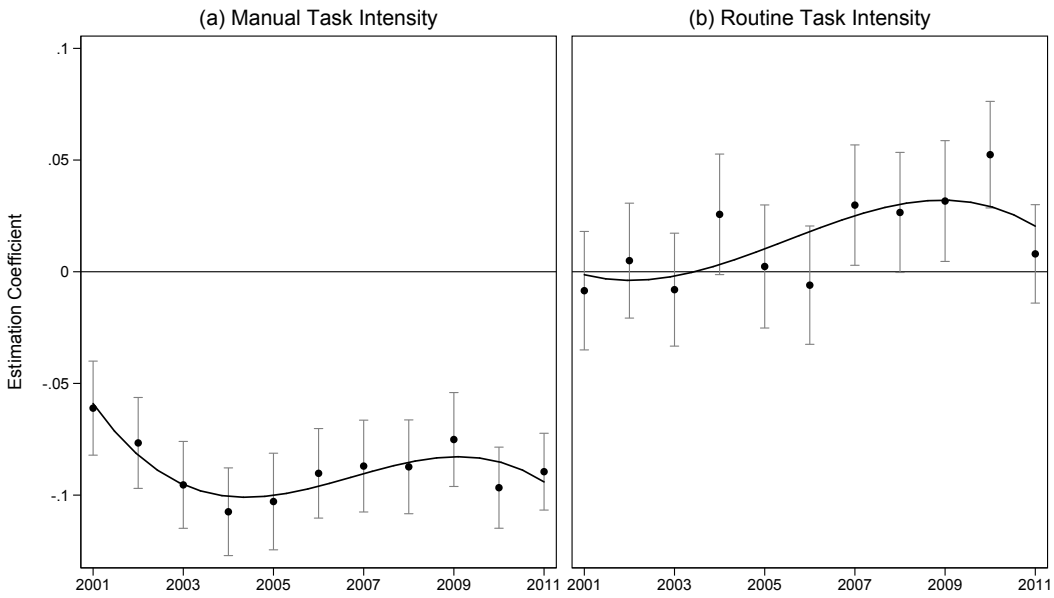


Notes: Solid lines are local polynomial smooth functions of degree 3, whereas spikes and cap lines represent the 95 percent confidence limits of estimation coefficients. Estimations are based on the full sample, which includes East and West German workers. Wage mobility is based on 3-year-time periods and calculated using cross-sectional weights.

In turn, interactive non-routine tasks show an increase in their impact on a worker's wage mobility between 2001 and 2004. Employees performing interactive non-routine tasks have experienced higher wage mobility by around 4 percentiles since 2005. Since abstract tasks are more present at the top of the skill distribution, the higher wage mobility is in line with the descriptive evidence as well as with the skill biased technical change hypothesis. However, the estimated coefficients of both of the remaining task types, cognitive routine and manual routine tasks, show an interesting empirical pattern. On the one hand, employees in manual routine occupations do not have a significantly different wage mobility compared to workers in manual non-routine occupations. On the other hand, workers performing cognitive routine tasks have a higher wage mobility and their wage mobility gap to workers in manual non-routine occupations has increased from 1.4 to 4.2 percentiles over time.

These findings indicate that the distinction in tasks does not depend on whether they are routine or non-routine, but rather depends on whether tasks are manual or non-manual. Since the task data set contains the task intensities for each occupation, this information is picked up in a further estimation instead of occupation's main task type (see Figure 13). In Panel (a), occupations' manual and non-manual task intensity are grouped together, whereas in Panel (b), distinction is made between an occupation's routine and non-routine task intensity. As a quick reminder, the sum of the five task intensities is equal to one for each occupation. Thus a decrease in, for example, routine task intensity is always accompanied by an increase in non-routine task intensity. Hence, if a worker's manual task intensity increases by one percentage point, his or her wage mobility decreases by around 0.1 percentile point in

Figure 13: Development of task intensity's impact on wage mobility over time (full sample)



Notes: Solid lines are local polynomial smooth functions of degree 3, whereas spikes and cap lines represent the 95 percent confidence limits of estimation coefficients. Estimations are based on the full sample, which includes East and West German workers. Wage mobility is based on 3-year-time periods and calculated using cross-sectional weights.

2011. Whereas there is a drop in the value of the estimation coefficient in Panel (a) at the beginning of the observation period, some recovery has occurred since 2004. However, the initial values can no longer be achieved. Switching the analysis to the distinction between routine and non-routine tasks, the effect of the routine tasks' intensity is mostly insignificant. Over time, however, the estimation coefficient slightly increases year by year. Combining both results, two conclusions can be drawn. First, workers who perform mainly manual tasks in their occupations show less upward wage mobility, regardless of whether their work activities consist of non-routine or routine-tasks. Since workers in manual routine and manual non-routine occupations do not differ significantly in their wage mobility, the prediction of the nuanced skill bias technical change hypothesis that manual non-routine workers should be beneficiaries of the computer and automation revolution can be denied for their upward wage mobility. Since the employment share of manual non-routine occupations is relatively high in the middle of the skill distribution, the wage losses of these occupations compensate for the wage gains of manual non-routine occupations at the lower end of the distribution. Second, routine and non-routine workers do not significantly differ in their wage mobility, on average. Since manual routine workers experience losses in their wage mobility and cognitive routine workers gain wage mobility, the observed insignificant effect is driven by these compensating effects. Ultimately, the suggestion that routine workers should experience less wage growth and consequently less wage mobility is true merely for manual routine workers. However, the increasing coefficient in Panel (b) indicates a rising wage mobility for cognitive routine workers over time.

4.3 Upward and Downward Mobility

In the previous analyses, wage mobility was measured as the difference between a worker's wage position in the base and the reporting year. Thus, the empirical results were interpreted as ceteris paribus effects on wage mobility over the whole wage mobility distribution. Since OLS estimations were applied, the impact of socio-economic and demographic characteristics was assumed to be constant across different wage mobility patterns. The following is an analysis of the extent to which there are asymmetries in the effects of the basic covariates on a worker's downward and upward wage mobility. For this purpose, the workers' wage mobility is measured as the difference in their wage decile between the base and the reporting year. In turn, the new dependent variable y_i aggregates these movements into three groups based on the aims of the investigation:

$$y_i = \begin{cases} 1 & \text{(downward mobility)}, & \text{if} \quad mob_i \in [-9,-1] \\ 2 & \text{(same decile/no mobility)}, & \text{if} \quad mob_i = 0 \\ 3 & \text{(upward mobility)}, & \text{if} \quad mob_i \in [1,9] \end{cases}, \tag{3}$$

where mob_i represents a worker's movement in wage deciles.[22] Thus, a distinction is made between workers who move to a lower decile, remain in the same decile, or move to an upper decile. Since these three categories are mutually exclusive, a multinomial logit model that estimates the effects of the basic covariates and the initial wage decile of workers on a worker's probability of experiencing the respective wage mobility types is applied. This enables the detection of divergent effects of covariates on a worker's probability of upward and downward wage mobility. In order to obtain a unique parameter identification in the multinomial logit models, the category "same decile/no mobility" is selected as the base category. Since the estimated coefficients are difficult to interpret and their magnitude has no meaning, the average marginal effects of a particular covariate on the respective probabilities are reported. In principle, the marginal effects on downward and upward mobility should have the opposite sign, since a positive impact on the probability of downward mobility should be accompanied by a negative impact on the probability of upward mobility. Thus, working in an occupation other than manager increases (decreases) a worker's probability of downward (upward) mobility (see Table 3).[23] However, some workers experience a higher impact in absolute terms on their upward mobility than their downward mobility. Whereas clerks and service workers have a 21.5-27 percent lower probability of upward mobility than managers, they have merely a 13-17.5 percent higher probability of downward mobility. Therefore, working as a clerk or a service worker has slightly higher relevance in relation to the chance to move upwards. The opposite applies to employees in the service industry. Their probability of downward (upward) mobility is 8.4 (5.7) percent higher (lower) than

[22] The measurement of mob_i differs from the original definition, since movements in wage percentiles lead to an insufficient number of observations in the middle category "same decile/no mobility".

[23] The estimation results for the other two time periods, 1995-1999 and 2010-2014, are given in Table 9 in the Appendix.

Table 3: Average marginal effects on upward and downward wage mobility in the 2005-2009 time period (full sample)

	Downward Mobility		Same Decile		Upward Mobility	
Individual Characteristics						
Age	0.001	(0.001)	0.001	(0.001)	-0.002	(0.001)**
Female	0.085	(0.018)***	0.002	(0.019)	-0.087	(0.017)***
Migrational Background	0.021	(0.018)	-0.033	(0.019)*	0.011	(0.018)
Low-Skilled			*reference*			
Medium-Skilled	-0.054	(0.029)*	-0.006	(0.028)	0.061	(0.023)***
High-Skilled	-0.166	(0.034)***	0.031	(0.036)	0.135	(0.032)***
Job Stability						
At Least 1 Job Change	0.062	(0.020)***	-0.088	(0.019)***	0.026	(0.019)
Unemployment Experience	0.198	(0.050)***	-0.134	(0.047)***	-0.065	(0.035)*
Job Tenure	0.001	(0.001)	-0.001	(0.001)	0.000	(0.001)
Employed Part-Time	0.070	(0.021)***	-0.070	(0.020)***	0.000	(0.019)
Employment Charateristics						
Firm Size: < 20			*reference*			
Firm Size: 20-200	-0.050	(0.022)**	0.004	(0.021)	0.046	(0.017)***
Firm Size: 200-2000	-0.087	(0.022)***	0.001	(0.023)	0.086	(0.020)***
Firm Size: > 2000	-0.122	(0.022)***	0.000	(0.024)	0.122	(0.022)***
Manufacturing			*reference*			
Agriculture	0.163	(0.109)	-0.035	(0.091)	-0.128	(0.072)*
Energy	-0.027	(0.056)	-0.088	(0.060)	0.115	(0.077)
Mining	0.108	(0.102)	-0.305	(0.063)***	0.197	(0.095)**
Construction	0.002	(0.021)	0.016	(0.025)	-0.018	(0.024)
Trade	0.139	(0.027)***	-0.013	(0.027)	-0.125	(0.024)***
Transport	0.061	(0.032)*	-0.031	(0.033)	-0.030	(0.032)
Bank,Insurance	-0.031	(0.031)	0.011	(0.038)	0.019	(0.041)
Services	0.084	(0.020)***	-0.027	(0.022)	-0.057	(0.021)***
Legislators/Senior Officials/Managers			*reference*			
Professionals	0.042	(0.027)	0.009	(0.034)	-0.051	(0.041)
Technicians/Associate Professionals	0.088	(0.025)***	0.052	(0.032)	-0.140	(0.037)***
Clerks	0.133	(0.030)***	0.082	(0.036)**	-0.215	(0.039)***
Service Workers/Shop and Market Sales Workers	0.175	(0.036)***	0.093	(0.040)**	-0.268	(0.041)***
Skilled Agricultural/Fishery Workers	0.230	(0.131)*	0.069	(0.130)	-0.299	(0.093)***
Craft and Related Trades Workers	0.254	(0.032)***	0.018	(0.036)	-0.272	(0.039)***
Plant and Machine Operators and Assemblers	0.310	(0.036)***	-0.017	(0.039)	-0.292	(0.040)***
Elementary Occupations	0.277	(0.045)***	0.039	(0.046)	-0.316	(0.042)***
Change of Occupation	0.028	(0.015)*	-0.030	(0.015)**	0.002	(0.015)
Change of Industry	0.013	(0.017)	-0.025	(0.018)	0.011	(0.017)
East-Germany	0.120	(0.019)***	-0.016	(0.018)	-0.104	(0.015)***
McFadden R^2			0.171			
AIC			7573.486			
BIC			8091.543			
Obs.			4096			

Notes: Multinomial logit estimations are applied to the full sample, which includes East and West German workers. Wage mobility categories are based on movements between deciles which are calculated using cross-sectional weights. Classification of industries is based on ISIC Rev. 3 and classification of occupations is based on ISCO88. Workers' initial wage deciles are included, but not reported. Robust standard errors are in parentheses. ***significant at 1 percent, **significant at 5 percent, *significant at 10 percent.

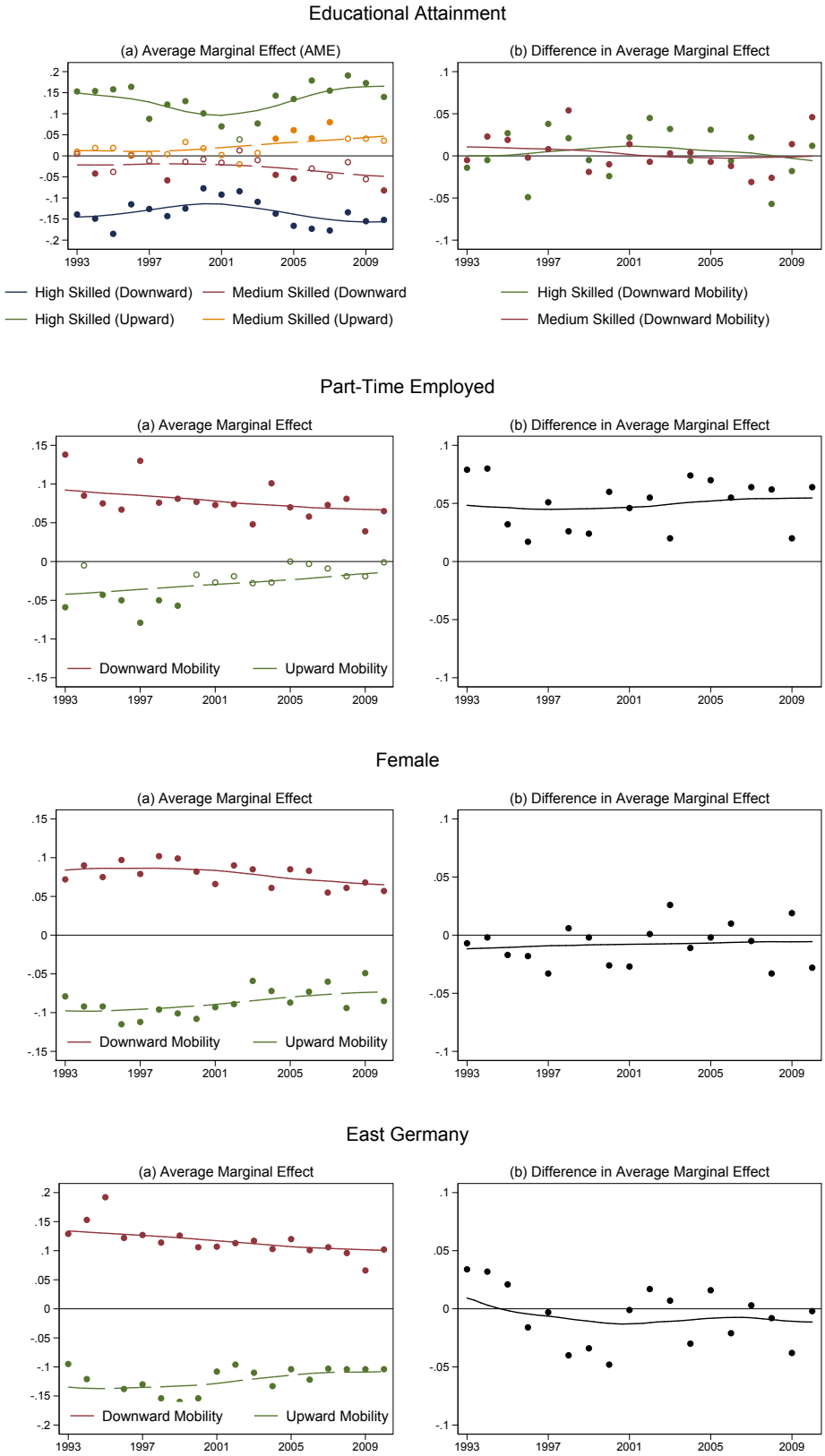
the respective probabilities of workers in the manufacturing industry. Interestingly, the impact of the firm size on downward and upward mobility is almost the same in absolute terms. The impact of unemployment experience on the probability of downward mobility is much higher than on the probability of upward mobility. Since unemployment experience almost exclusively takes positive values for downwards mobile and immobile workers, the

results confirm that unemployment spells are highly correlated with downwards mobility and accompanied with wage losses. Furthermore, a job change has significant effect on the probability of downward and no mobility, but no significant impact on upward mobility. This confirms the insignificant effect of job changes on a worker's wage mobility at the beginning of the section and provides more detailed information. On the one hand, a positive correlation between job changes and upward mobility is expected due to the standard job search theory, which predicts that job-to-job transitions are mainly voluntary and are accompanied by wage increases (Pissarides, 1994). On the other hand, workers might switch to low-wage employment due to family reasons or imminent risk of unemployment, which is correlated with downward mobility. Since only the marginal effects on downward mobility and no mobility are significant, the explanations are twofold. First, a positive correlation of job changes with downward mobility indicates that a significant fraction of workplace changes are involuntary due to family reasons or unemployment risks. Second, the negative correlation with immobility suggests that voluntary job changes in order to achieve higher wages do not even guarantee moving up within the same decile.[24] Thus, the results indicate that job changes tend to be associated with a loss in wages and a downward wage mobility.

In order to compare the estimation results of wage mobility patterns with the estimation results of wage mobility, the development of the marginal effects of selected covariates is illustrated (see Figure 14). Panel (a) shows the average marginal effects of the respective exogenous variables on the probabilities and Panel (b) represents the difference in average marginal effects on downward and upward wage mobility. Considering the development of the average marginal effects of a worker's educational attainment on his or her wage mobility, the previous findings can be confirmed. High-skilled workers and medium-skilled workers have a lower (higher) probability of downward (upward) wage mobility than low-skilled workers. The average marginal effects are greater, in absolute terms, for the high-skilled than for the medium-skilled. Furthermore, both smoothed functions of the difference in average marginal effects are close to zero. Thus, there is no clear difference in the magnitude of the average marginal effects on downward and upward mobility. Moreover, average marginal effects of high-skilled workers show a slight hump shape (u-shape) with respect to downward (upward) wage mobility, which has already been detected in the estimation of wage mobility. Additionally, there is no clear difference in the average marginal effects of the gender variable. Women had an 8.5 (8.7) higher (lower) probability of downward (upward) wage mobility than men in 2010. Living in East Germany increases (decreases) a worker's probability of downward (upward) mobility. However, the marginal effects on downward mobility were higher at the beginning of the observation period. Taking a comparison between the marginal effects of part-time employment on downward and upward mobility detects that both effects decreased in magnitude over time. In turn, the difference in the marginal effects

[24] A positive effect on the immobility would be consistent with voluntary and involuntary job changes. On the one hand, a worker's wage increase due to the job change is too small to push him or her into the next decile. On the other hand, a worker's wage loss due to a job change is small enough to keep him or her within the same decile.

Figure 14: Change of task usage over the skill distribution, 2001-2013 (full sample)



Notes: Multinomial logit estimations are applied to the full sample, which includes East and West German workers. Wage mobility categories are based on movements between deciles which are calculated using cross-sectional weights. Hollow circles represent insignificant average marginal effects, whereas filled circles represent average marginal effects which are at least significant at 10 percent. Solid and dashed lines are local polynomial smooth functions of degree 3.

is consistently positive, i.e. the marginal effects on downward mobility are higher than on upward mobility. Since a convergence between part-time and full-time employment in wage mobility has been detected earlier, the results of the wage mobility patterns suggest that this development is mainly driven due to a convergence in the probability of upward mobility. Hence, part-time workers still have a higher probability of downward mobility than full-time workers, but with regard to upward mobility, both worker types have nearly identical probabilities at the present time.

5 Conclusion

In the aftermath of the financial crisis, the trend in German wage inequality received broad international attention, since wage inequality had started to stabilize in Germany at this point, in contrast to other industrialized countries. The decline in the indexed 5/1 wage decile ratio and the strong increase in the indexed 9/5 wage decile ratio since 2006 contributed to this development and even culminated in a polarization of wage growth along the wage distribution between 2006 and 2013. In contrast, since the beginning of the 2000s wage mobility has strongly decreased and the workers' state dependence in initial ranks has increased in West and East Germany. Over an observation period of 30 years, the unemployment duration and the kind of occupation of a worker has increased in importance for their wage mobility, whereas the influence of gender, living in East Germany, and working part-time has lost importance. Since the relevance of occupation-specific human capital has strengthened over time, a consequential follow-up question is whether the wage mobility estimates and the wage polarization between 2006 and 2013 are attributable to the predictions of the nuanced skill biased technical change. Although there is a polarization of wage and employment growth along the skill distribution, cognitive tasks and manual routine tasks are more pronounced at the top and in the middle of the skill distribution, respectively. Regarding the tasks' impact on a worker's wage mobility, the polarization hypothesis can merely partially confirmed. First, workers who perform mainly manual non-routine tasks do note differ in their wage mobility from workers in manual routine occupations over the entire observation period. Second, workers in cognitive routine occupations show a higher and also increasing wage mobility compared to manual non-routine workers. Therefore, wage losses of cognitive routine workers in the middle of the skill distribution are overcompensated through wage gains at the top. In converse, wage gains of manual non-routine workers at the bottom of the skill distribution are overcompensated through wage losses in the middle. In conclusion, the prediction of the polarization hypothesis that non-routine workers (routine workers) should be beneficiaries (losers) of the computer and automation revolution can be denied for manual non-routine worker (cognitive routine workers) with respect to upward wage mobility. Ultimately, the suggestion that routine workers should experience less wage growth and consequently less wage mobility is true merely for manual routine workers.

Regarding the drivers of wage mobility at all, the increasing influence of unemployment

experience within the fixed 4-year time periods is ground for some concern about the benefits of re-employment and necessitates a re-examination of labor market policies in Germany. Although some fundamental reforms were made at the beginning of the 2000s, and the current unemployment rate is at a historically low level, the increasing wage mobility penalty for each additional month of unemployment indicates that even short periods of unemployment might strongly reduce a worker's potential to reach his or her initial relative wage position after four years. Since short periods of unemployment are more pronounced for part-time workers than full-time workers in Germany, the increasing impact of unemployment experience on a worker's wage mobility might be due to the institutional setting of the labor market. This is also reflected in the convergence of part-time and full-time workers in their wage mobility over time, which is, however, mainly driven by the convergence in their upward mobility. Thus, part-time worker are still significantly more downward mobile, whereas full-time workers' upward mobility has shrunk over time. In particular, the design of the so-called mini- and midijobs, as well as the unemployment benefit system, create incentives to remain in lower-paying, part-time jobs because the transition to a better paying, full-time job would result in lower net incomes, especially for secondary earners of a household, due to the expiry of tax advantages and the loss of advantages of the social security system. Furthermore, attention should be given to the significant difference in wage mobility between men and women. Although there has been a decline in the gender wage mobility gap over time, men still had a 4 percentile higher wage mobility than women in 2010. Since a worker's wage mobility depends, among other things, on his or her wage growth within the fixed time period, this indicates that there is a discrepancy in the wage growth rate between the sexes. Therefore, future research should supplement the analysis of the cross-sectional gender wage gap with the gender wage mobility gap.

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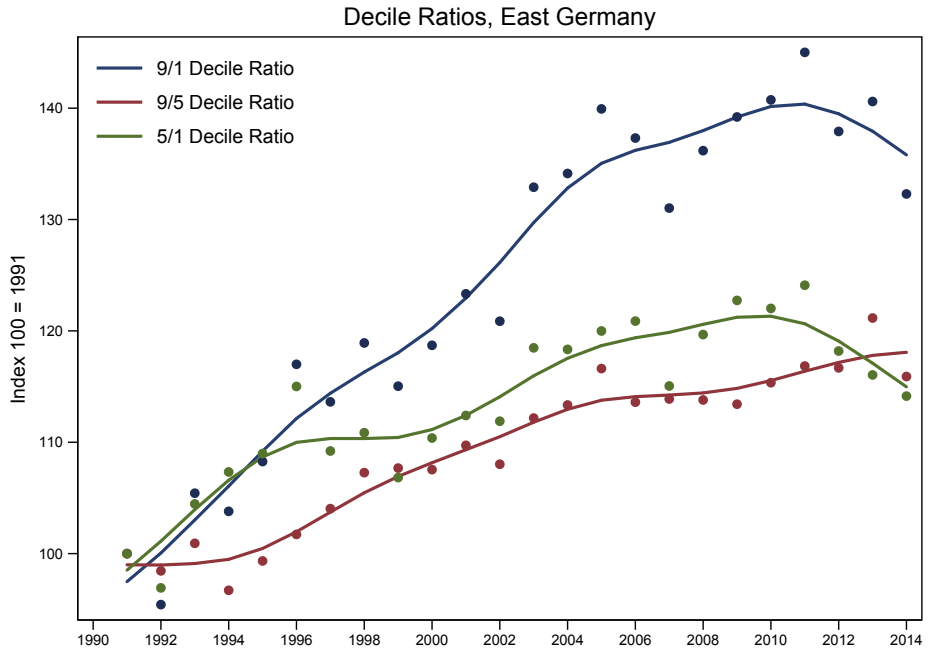
Appendix

Figure 15: Development of real hourly wage decile ratios, East Germany



Notes: Decile ratios are indexed on 1991 and are based on real hourly wages weighted with the corresponding cross-sectional weights. Solid lines represent the trend component of the applied Hodrick-Prescott filter (Hodrick and Prescott, 1997). Since annual data are applied, the smoothing parameter is $\lambda = 6.25$ according to the rule-of-thumb in Ravn and Uhlig (2002).

Table 4: Number of wage mobility observations per 4-year time period

Base Year	West Germany	East Germany	Total
1984	2669		
1985	2563		
1986	2462		
1987	2559		
1988	2467		
1989	2460		
1990	2371		
1991	2413	1243	3656
1992	2350	1150	3500
1993	2307	1084	3391
1994	2211	1045	3256
1995	2380	1057	3437
1996	2332	1025	3357
1997	2295	954	3249
1998	2463	993	3456
1999	2432	958	3390
2000	3880	1328	5208
2001	3753	1262	5015
2002	3921	1259	5180
2003	3802	1212	5014
2004	3586	1183	4769
2005	3252	1113	4365
2006	3270	1116	4386
2007	3183	1124	4307
2008	2833	1031	3864
2009	2642	955	3597
2010	3680	1136	4816

Notes: Only workers who have valid real hourly wages in both the base year and the reporting year are taken into account.

Table 5: Definition of educational attainment in the estimations

Educational Category	Feature	CASMIN categories	
Low-Skilled	no completed apprenticeship	1a	inadequately completed
	or	1b	general elementary school
	no high school diploma	2b	intermediate general qualification
Medium-Skilled	completed apprenticeship	1c	basic vocational qualification
		2a	intermediate vocational
	or high school diploma	2c(voc)	vocational maturity certificate
		2c(gen)	general maturity certificate
High-Skilled	university degree	3a	lowert tertiary education
		3b	higher tertiary education

Notes: Design is based on Zenzen (2013).

Table 6: Results of the Heckman selection model

	Correlation		**Selection Equation**			
	atan ρ		*Married*		*Number of Kid(s) at Home*	
1993	-.277	(.263)	-.156	(.072)**	.155	(.03)***
1994	-.083	(.187)	-.104	(.074)	.091	(.03)***
1995	-.153	(.186)	-.115	(.073)	.159	(.033)***
1996	-.444	(.155)***	-.201	(.077)***	.109	(.034)***
1997	-.209	(.287)	-.074	(.076)	.106	(.037)***
1998	-.137	(.28)	-.104	(.076)	.051	(.037)
1999	-.036	(.952)	.033	(.071)	.01	(.034)
2000	-.126	(.161)	.145	(.056)**	.035	(.028)
2001	-.136	(.178)	.182	(.059)***	.04	(.029)
2002	-.232	(.153)	.219	(.06)***	.045	(.03)
2003	-.235	(.208)	.132	(.07)*	.015	(.035)
2004	-.084	(.547)	.063	(.079)	.021	(.039)
2005	-.027	(.605)	.094	(.087)	.03	(.046)
2006	-.374	(.154)**	.066	(.077)	.055	(.041)
2007	.098	(.294)	.096	(.087)	.074	(.049)
2008	.093	(.22)	.288	(.09)***	.047	(.054)
2009	-.266	(.193)	.127	(.095)	.148	(.062)**
2010	.101	(.288)	.223	(.087)**	.017	(.04)

Notes: Estimations are based on the full sample, which includes East and West German workers. Wage mobility is calculated using cross-sectional weights. Selection variables are a worker's marital status and the number of kids in his or her household. Correlation of the error terms between wage mobility and labor market participation (in the reporting year) equation is represented by $\text{atan}\,\rho = \frac{1}{2}\ln\left(\frac{1+\rho}{1-\rho}\right)$, which yields the inverse hyperbolic tangent of ρ. Classification of industries is based on NACE Rev. 1, where "agriculture", "fishing", and "mining" are combined into a category and "other community activities", "private households", and "extra-territorial organization" are combined into "other industries". The classification of occupations is based on ISCO88. Workers' initial wage percentiles or ranks are included, but not reported. Standard errors are in parentheses. ***significant at 1 percent, **significant at 5 percent, *significant at 10 percent.

Table 7: Decomposition of overall wage inequality by West and East Germany

	Mean Logarithmic Deviation			Contribution to Overall Inequality	
Year	*Germany*	*East Germany*	*West Germany*	*Between-Region Inequality*	*Within-Region Inequality*
1991	0.12	0.06	0.08	33.19	66.81
1992	0.11	0.07	0.09	21.93	78.07
1993	0.11	0.08	0.09	15.97	84.03
1994	0.09	0.07	0.08	13.50	86.50
1995	0.11	0.08	0.10	11.39	88.61
1996	0.09	0.08	0.09	11.36	88.64
1997	0.10	0.09	0.09	8.84	91.16
1998	0.10	0.09	0.09	9.25	90.75
1999	0.10	0.08	0.09	9.98	90.02
2000	0.10	0.09	0.09	7.51	92.49
2001	0.10	0.09	0.09	7.02	92.98
2002	0.10	0.09	0.10	6.23	93.77
2003	0.10	0.11	0.10	5.82	94.18
2004	0.10	0.11	0.10	5.04	94.96
2005	0.11	0.12	0.10	4.77	95.23
2006	0.11	0.10	0.11	5.26	94.74
2007	0.11	0.11	0.10	5.72	94.28
2008	0.11	0.10	0.10	6.16	93.84
2009	0.12	0.11	0.11	5.43	94.57
2010	0.12	0.12	0.11	4.49	95.51
2011	0.12	0.12	0.11	5.36	94.64
2012	0.11	0.12	0.11	4.06	95.94
2013	0.12	0.12	0.11	4.64	95.36
2014	0.11	0.11	0.11	4.41	95.59

Notes: Calculations are based on the mean logarithmic deviation as a measure of wage inequality. Full, West German, and East German samples are applied separately. Contributions are expressed in percentage.

Table 8: Determinants of wage mobility in different 4-year time periods using detailed industries (full sample)

	1995-1999		2005-2009		2010-2014	
Individual Characteristics						
Age	-0.124	(0.040)***	-0.115	(0.038)***	-0.142	(0.034)***
Female	-5.395	(0.844)***	-4.250	(0.661)***	-4.105	(0.614)***
Migrational Background	-1.350	(0.793)*	-0.692	(0.715)	-0.967	(0.625)
Low-Skilled			*reference*			
Medium-Skilled	2.130	(1.017)**	2.542	(1.009)**	2.962	(1.008)***
High-Skilled	7.740	(1.487)***	7.382	(1.289)***	7.875	(1.227)***
Job Stability						
At Least 1 Job Change	-1.132	(0.880)	-0.729	(0.803)	0.814	(0.658)
Unemployment Experience	-3.951	(1.371)***	-5.258	(1.666)***	-6.149	(1.361)***
Job Tenure	0.045	(0.040)	0.034	(0.036)	0.074	(0.033)**
Employed Part-Time	-3.083	(1.083)***	-2.866	(0.801)***	-1.689	(0.690)**
Employment Characteristics						
Firm Size: < 20			*reference*			
Firm Size: 20-200	1.729	(0.879)**	2.662	(0.762)***	1.782	(0.699)**
Firm Size: 200-2000	4.786	(0.933)***	5.262	(0.873)***	4.280	(0.771)***
Firm Size: > 2000	7.090	(0.972)***	6.777	(0.886)***	5.909	(0.778)***
Manufacturing			*reference*			
Agriculture/Fishing/Mining	-5.674	(2.140)***	-3.873	(2.318)*	-0.542	(2.362)
Electricity/Gas/Water	3.948	(2.771)	-0.735	(2.479)	-2.493	(2.245)
Construction	-2.150	(1.075)**	-0.624	(1.240)	-3.468	(1.012)***
Wholesale and Retail Trade	-2.789	(1.179)**	-5.830	(0.935)***	-5.706	(0.873)***
Hotels and Restaurants	-3.815	(2.548)	-7.804	(1.882)***	-8.691	(1.824)***
Transport, Storage, and Communication	-2.698	(1.382)*	-2.512	(1.275)**	-2.745	(1.094)**
Financial Intermediation	2.053	(1.465)	3.048	(1.164)***	0.118	(1.148)
Real Estate, Renting, and Business Activities	2.871	(1.443)**	-1.456	(1.004)	-1.393	(0.872)
Public Administration/Social Security	-1.709	(1.280)	-1.373	(1.076)	-1.554	(0.992)
Education	0.090	(1.566)	-1.332	(1.407)	0.389	(1.226)
Health and Social Work	-2.201	(1.241)*	-3.874	(0.997)***	-4.674	(0.874)***
Other Industries	1.705	(1.852)	-2.338	(1.484)	-3.452	(1.322)***
Legislators/Senior Officials/Managers			*reference*			
Professionals	3.552	(1.901)*	-0.442	(1.200)	0.927	(1.101)
Technicians/Associate Professionals	-2.756	(1.766)	-4.660	(1.192)***	-2.661	(1.104)**
Clerks	-3.842	(1.861)**	-8.326	(1.336)***	-6.251	(1.260)***
Service Workers/Shop and Market Sales Workers	-7.755	(2.168)***	-10.817	(1.467)***	-6.884	(1.446)***
Skilled Agricultural/Fishery Workers	-10.241	(3.183)***	-15.387	(3.417)***	-14.030	(2.491)***
Craft and Related Trades Workers	-8.593	(1.847)***	-11.071	(1.382)***	-9.331	(1.279)***
Plant and Machine Operators and Assemblers	-9.701	(1.909)***	-13.556	(1.505)***	-11.064	(1.425)***
Elementary Occupations	-12.123	(2.138)***	-13.316	(1.617)***	-10.042	(1.573)***
Change of Occupation	-0.005	(0.655)	-0.582	(0.560)	0.223	(0.513)
Change of Industry	-0.157	(0.746)	-0.191	(0.663)	-0.734	(0.602)
East-Germany	-10.585	(0.981)***	-6.190	(0.703)***	-5.961	(0.620)***
R^2	0.275		0.235		0.236	
Obs	3263		4035		4469	

Notes: Estimations are based on the full sample, which includes East and West German workers. Wage mobility is calculated using cross-sectional weights. Classification of industries is based on NACE Rev. 1, where "agriculture", "fishing", and "mining" are combined into a category and "other community activities", "private households", and "extra-territorial organization" are combined into "other industries". The classification of occupations is based on ISCO88. Workers' initial wage percentiles or ranks are included, but not reported. Robust standard errors are in parentheses. ***significant at 1 percent, **significant at 5 percent, *significant at 10 percent.

Table 9: Average marginal effects on upward and downward wage mobility in the 1995-1999 and 2010-2014 time periods (full sample)

	1995 - 1999						2010 - 2014					
	Downward Mobility		Same Decile		Upward Mobility		Downward Mobility		Same Decile		Upward Mobility	
Individual Characteristics												
Age	0.001	(0.001)	0.003	(0.001)***	-0.005	(0.001)***	0.002	(0.001)**	0.002	(0.001)**	-0.004	(0.001)***
Female	0.075	(0.020)***	0.017	(0.021)	-0.092	(0.020)***	0.057	(0.017)***	0.028	(0.018)	-0.085	(0.016)***
Migrational Background	0.016	(0.019)	0.006	(0.020)	-0.022	(0.020)	0.006	(0.017)	0.019	(0.018)	-0.025	(0.016)
Low-Skilled						*reference*						
Medium-Skilled	-0.038	(0.024)	0.019	(0.025)	0.019	(0.023)	-0.082	(0.031)***	0.045	(0.029)	0.036	(0.024)
High-Skilled	-0.185	(0.031)***	0.027	(0.036)	0.158	(0.036)***	-0.152	(0.036)***	0.012	(0.035)	0.140	(0.031)***
Job Stability												
At Least 1 Job Change	0.061	(0.021)***	-0.058	(0.020)***	-0.003	(0.020)	0.000	(0.017)	-0.050	(0.017)***	0.050	(0.016)***
Unemployment Experience	0.142	(0.032)***	-0.060	(0.032)*	-0.082	(0.030)***	0.235	(0.046)***	-0.077	(0.045)*	-0.158	(0.037)***
Job Tenure	0.000	(0.001)	-0.001	(0.001)	0.000	(0.001)	0.000	(0.001)	-0.001	(0.001)	0.000	(0.001)
Employed Part-Time	0.075	(0.026)***	-0.033	(0.024)	-0.043	(0.024)*	0.065	(0.019)***	-0.064	(0.019)***	-0.001	(0.017)
Employment Characteristics												
Firm Size: < 20						*reference*						
Firm Size: 20-200	-0.034	(0.023)	-0.019	(0.023)	0.053	(0.020)**	-0.031	(0.020)	-0.004	(0.020)	0.035	(0.016)**
Firm Size: 200-2000	-0.089	(0.024)***	-0.017	(0.025)	0.106	(0.023)***	-0.079	(0.021)***	-0.006	(0.022)	0.084	(0.019)***
Firm Size: > 2000	-0.133	(0.025)***	-0.018	(0.026)	0.151	(0.025)***	-0.121	(0.021)***	-0.004	(0.022)	0.125	(0.020)***
Manufacturing						*reference*						
Agriculture	0.238	(0.069)***	-0.059	(0.057)	-0.179	(0.051)***	0.028	(0.081)	0.031	(0.075)	-0.059	(0.063)
Energy	-0.064	(0.050)	-0.096	(0.073)	0.160	(0.070)**	0.043	(0.049)	-0.065	(0.053)	0.022	(0.054)
Mining	-0.006	(0.094)	0.001	(0.116)	0.004	(0.091)	-0.139	(0.014)***	-0.398	(0.016)***	0.536	(0.016)***
Construction	0.012	(0.022)	-0.019	(0.025)	0.006	(0.025)	0.028	(0.021)	-0.021	(0.024)	-0.007	(0.023)
Trade	0.078	(0.030)**	-0.042	(0.030)	-0.036	(0.029)	0.115	(0.026)***	-0.029	(0.026)	-0.085	(0.023)***
Transport	0.038	(0.037)	-0.041	(0.037)	0.003	(0.035)	0.058	(0.031)*	-0.049	(0.032)	-0.009	(0.032)
Bank,Insurance	-0.009	(0.038)	-0.003	(0.043)	0.012	(0.043)	0.033	(0.032)	-0.009	(0.037)	-0.024	(0.037)
Services	0.005	(0.022)	-0.019	(0.025)	0.015	(0.024)	0.074	(0.020)***	-0.024	(0.021)	-0.050	(0.020)**
Legislators/Senior Officials/Managers						*reference*						
Professionals	-0.035	(0.037)	0.020	(0.044)	0.015	(0.057)	-0.030	(0.028)	0.017	(0.034)	0.012	(0.042)
Technicians/Associate Professionals	0.054	(0.036)	0.091	(0.040)**	-0.145	(0.051)***	0.034	(0.028)	0.040	(0.032)	-0.075	(0.038)**
Clerks	0.003	(0.038)	0.148	(0.043)***	-0.151	(0.052)***	0.119	(0.032)***	0.041	(0.036)	-0.161	(0.040)***
Service Workers/Shop and Market Sales Workers	0.188	(0.047)***	0.050	(0.047)	-0.238	(0.054)***	0.153	(0.039)***	0.043	(0.040)	-0.196	(0.041)***
Skilled Agricultural/Fishery Workers	0.135	(0.109)	0.086	(0.109)	-0.221	(0.102)**	0.398	(0.089)***	-0.111	(0.070)	-0.287	(0.062)***
Craft and Related Trades Workers	0.167	(0.038)***	0.039	(0.041)	-0.206	(0.052)***	0.202	(0.034)***	-0.007	(0.036)	-0.195	(0.039)***
Plant and Machine Operators and Assemblers	0.163	(0.042)***	0.076	(0.044)*	-0.239	(0.053)***	0.215	(0.040)***	0.006	(0.040)	-0.221	(0.041)***
Elementary Occupations	0.196	(0.047)***	0.083	(0.048)*	-0.279	(0.054)***	0.216	(0.045)***	0.008	(0.044)	-0.225	(0.042)***
Change of Occupation	0.002	(0.016)	-0.016	(0.018)	0.014	(0.017)	-0.015	(0.014)	0.010	(0.015)	0.005	(0.014)
Change of Industry	-0.001	(0.017)	-0.020	(0.018)	0.020	(0.018)	0.019	(0.016)	-0.020	(0.017)	0.001	(0.015)
East-Germany	0.192	(0.021)***	-0.021	(0.020)	-0.171	(0.018)***	0.102	(0.018)***	0.003	(0.018)	-0.104	(0.014)***
McFadden R2			0.176						0.167			
AIC			6175.153						8488.382			
BIC			6676.061						9009.008			
Obs.			3323						4571			

Notes: Estimations are based on the full sample, which includes East and West German workers. Wage mobility categories are based on movements between deciles which are calculated using cross-sectional weights. Classification of industries is based on ISIC Rev. 3 and classification of occupations is based on ISCO88. Workers' initial wage deciles are included, but not reported. Robust standard errors are in parentheses. ***significant at 1 percent, **significant at 5 percent, *significant at 10 percent.