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Abstract

We examine the development of worker-firm matching over the career due to job mobility. Using administrative employer-employee data covering the universe of German employees, we measure the degree of assortative matching as the correlation of worker and firm quality measures obtained from a wage decomposition in the style of Abowd/Kramarz/Margolis (1999). We also introduce a novel measure based on the distance between the estimates of worker and firm quality. Both measures indicate that the degree of assortative matching, on average, increases with each job move. For high-quality workers, this can be explained by job ladder models as these workers move to higher-quality firms. Low-quality workers are matched less assortatively at the beginning of their careers, but also manage to climb the job ladder at first. For this group, the increase in assortative matching increases after the third job, when they fall down the job ladder. Changes in worker-firm matching are also relevant for the extent of life cycle inequality. We estimate that the increase in assortative matching accounts for around 25 percent of the increase in wage inequality over the life cycle.

Zusammenfassung

Wir analysieren, wie sich das Matching zwischen Betrieben und Beschäftigten über das Erwerbsleben durch Jobmobilität verändert. Wir nutzen deutsche administrative Daten, die sowohl Informationen über Beschäftigte als auch Betriebe enthalten. Um assortatives Matching zu messen, berechnen wir die Korrelation zwischen zeitkonstanten Lohnkomponenten von Betrieben und Beschäftigten, welche wir aus einer Lohndekomposition im Stil von Abowd/Kramarz/Margolis (1999) ziehen. Zudem benutzen wir ein neues MaSS für assortatives Matching, welches auf der Distanz zwischen diesen Lohnkomponenten basiert. Beide MaSSe zeigen, dass der Grad des assortativen Matchings im Durchschnitt mit jedem weiteren Betriebswechsel ansteigt. Bei Beschäftigten mit einer hohen zeitkonstanten Lohnkomponente kann dies durch Job Ladder Modelle erklärt werden, denn die Beschäftigten bewegen sich zu Firmen mit höheren Lohnkomponenten. Dahingegen sind Beschäftigte mit niedrigerer Lohnkomponente am Anfang des Erwerbslebens in weniger assortativen Matches zu finden, da sie es ebenfalls schaffen, zu Beginn die Job Ladder hinaufzuklettern. Für sie beginnt der Anstieg des assortativen Matchings erst nach dem dritten Job, wenn sie von der Job Ladder fallen. Die Entwicklung des assortativen Matchings ist zudem relevant für die Lohnungleichheit im Lebensverlauf. Wir zeigen, dass der Anstieg des assortativen Matchings circa 25 Prozent des Anstiegs der Lohnungleichheit im Lebensverlauf erklären kann.

JEL

J23, J24, J31, J62

Keywords

Assortative Matching, Wage Decomposition, Job Mobility, Life Cycle, Wage Inequality, Firms

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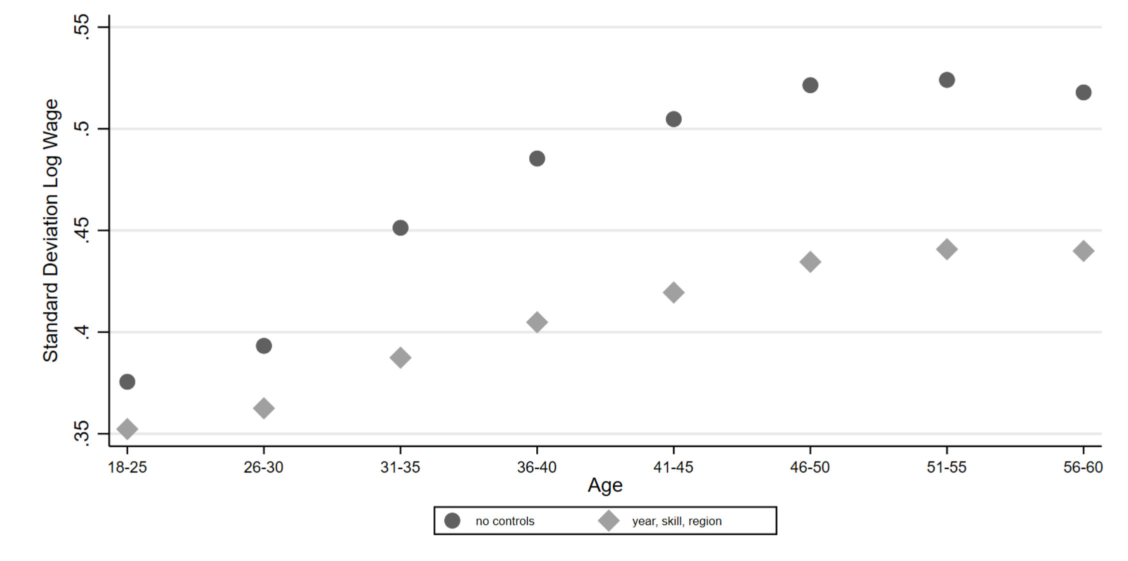
1 Introduction

In most countries around the world, there has been a secular increase of wage inequality in the past decades. A large number of studies document that this stems from increasing inequality of wage components that are largely time-constant from the individual perspective: worker-specific ability and firm-specific wage premiums, as well as their co-variation, commonly referred to as assortative matching (Abowd/Kramarz/Margolis, 1999; Card/Heining/Kline, 2013; Torres et al., 2018). While the role of worker-firm matching has been investigated in the context of rising aggregate wage inequality, less attention has been paid to the role of assortative matching at the intensive margin, namely over individual workers' careers. More precisely, the existing literature on assortative matching has been silent about the degree of assortative matching of individuals at their labor market entry and its evolution over time. An increase in the degree of assortative worker-firm matching could happen if workers switch between firms to climb the job ladder or fall down the job ladder because previously incomplete information on their ability has been revealed on the job.

In this paper, we explore assortative matching and its development as a component of life cycle wage inequality. Specifically, we ask whether workers and firms are matched assortatively and whether the degree of assortative matching increases with job mobility. Figure 1 shows how wage inequality increases with age. If worker-firm matches become more assortative over the life cycle, part of the increase in wage inequality within a cohort could be due to the specific movement of workers towards firms that match their own quality. Our main finding is that job matches become more assortative with each job move. This pattern is seen most clearly for high-wage workers, which is in line with job ladder models. For low-wage workers, by contrast, it emerges only after a few job moves. This can be explained by incomplete and asymmetric information on a worker's low ability that can be inferred by future employers only from a pattern of (involuntary) job switches. Overall, this contributes to increasing wage inequality over the life cycle.

We use rich administrative data covering the universe of labor market participants in Germany for the years 1995-2019 and decompose wages into a firm-specific, a worker-specific component, and an error term following Abowd/Kramarz/Margolis (1999: henceforth AKM). Next, we determine the degree of assortative worker-firm matching in two different ways. First, computing the correlation between the estimated AKM firm and worker fixed effects is the traditional way. Separate correlations by job numbers allow comparing the extent of assortative matching over workers' careers. We develop a second, novel, approach to quantify assortative worker-firm matching which allows determining the degree of assortative matching for every individual worker-firm pair. By ranking all workers

Figure 1: Wage Inequality over the Life Cycle



Note: The figure shows the standard deviation of log wages for different age groups.
Source: IEB, own calculations. ©IAB

and firms based on their estimated AKM fixed effect and assigning them to one out of 100,000 bins respectively, we compute the distance between worker and firm quality based on the difference in their rank in the estimated worker and firm fixed effects distribution.

We find three main results. First, using the traditional measure, we find evidence for assortative matching that is comparable in size to previous studies that are based on essentially the same data (Card/Heining/Kline, 2013; Lochner/Schulz, 2022). The correlation between worker and firm quality amounts to 0.352. Further, we find that, on average, the degree of worker-firm matching increases with each job move. While the correlation between estimated worker and firm fixed effects amounts to 0.293 in the first job, it increases to 0.405 for workers in their sixth job. Using our novel approach to quantify assortative matching at the individual level, we find that the average distance between worker and firm quality decreases over the career which indicates that matches tend to become more assortative over the career. One advantage of this individual measure is that it allows to control for worker heterogeneity in the analysis, which addresses changes in the composition of the workforce over the life cycle. When controlling for (un)observed characteristics, worker-firm matches become more assortative starting in the fourth job. Second, we find different patterns by worker groups. While for low-wage workers the distance increases at the beginning of the career, resulting in less assortative matches, high-wage workers manage to improve in terms of assortative matching right from the first job. Third, a counterfactual exercise suggests that the development of assortative matching contributes to life cycle wage inequality. We compute counterfactual variances of wages by fixing the degree of assortative matching at the initial level at the beginning of the employment course. We find that the increasing pattern of assortative matching due to job mobility accounts for 20 to 30 percent of the rise in wage inequality over the life cycle.

Our results are compatible with job ladder models like the wage posting models of Burdett/Mortensen (1998) and Christensen et al. (2005) where employees search on the job and accept any job that offers a higher wage than the current job. The job ladder arises because firms differ with respect to the constant wage that they offer to all their otherwise equal workers, which is compatible to the AKM firm fixed effect in our setting (Kahn/McEntarfer, 2014). In line with the exogenous mobility assumption of the AKM model, workers do not search in order to find a job that improves the idiosyncratic match (as in, e.g., Flinn, 2006; Haltiwanger/Hyatt/McEntarfer, 2018), which is part of the error term in the AKM model. This assumption has been shown to hold, for example, in Germany (Card/Heining/Kline, 2013), Portugal (Card/Cardoso/Kline, 2016), and Italy (Macis/Schivardi, 2016), but may be violated in other countries.[1]

The job ladder model is best suited to explain why (relatively high-ability) workers voluntarily move to higher-paying firms (Lise/Robin, 2017). Our results are also partly driven by (relatively low-ability) workers moving to lower-paying firms. This behavior is also compatible with the job ladder under the assumption of incomplete and asymmetric information. Consider a model where worker ability is private information of workers but is learned by employers only after a period of employment as in Gibbons/Katz (1991) and Laing (1994). If firms can choose who to lay off, they will lay off their least able workers first and replace them with better workers. The event of a layoff provides information on the worker's low ability also to other potential employers. Since the low ability has now been revealed, the worker will not find an equally-paying new job and has to accept a lower-paid job. In our setting, this comes through a move down the job ladder.[2] In practice, the negative signal might become stronger with each job move over a low-ability worker's career. Consequently, low-ability workers can climb up the job ladder by masking their ability early in their career, but this becomes increasingly difficult, causing them to climb down eventually.

We contribute to three partly overlapping strands of literature. First, our study adds to existing research on assortative matching on the labor market. Empirical studies find somewhat mixed evidence of matching between workers and firms. The sign and strength of assortative matching seems to differ between countries (Abowd/Kramarz/Margolis, 1999; Abowd et al., 2004; Woodcock, 2008; Gruetter/Lalive, 2009; Card/Heining/Kline, 2013; Song et al., 2019). More recently, Bonhomme et al. (2023) showed the importance of limited

[1] For example, Jinkins/Morin (2018) show that job-to-job mobility of Danish workers is mostly driven by improving match quality. Still, increasing assortative matching has been a major driver of increasing wage inequality also in Denmark (Morin, 2023).

[2] Fackler/Mueller/Stegmaier (2021) show that wage losses due to displacement from German plants indeed stem mostly from losses in firm wage premiums.

mobility bias for these kind of analyses and show that after correcting for the bias, the correlations reflecting worker-firm matching are positive and strong. This could explain the negative correlations found in earlier studies. As mentioned, assortative matching is often examined in the context of rising wage inequality over time. Alongside firm- and worker heterogeneity, it is found to explain approximately one third of wage variation (Card/Heining/Kline, 2013; Torres et al., 2018; Song et al., 2019). Woodcock (2008) and Sørensen/Vejlin (2013) expand the standard model containing worker and firm fixed effects by a match-specific effect and find that worker-firm matching explains around 16 percent of U.S. wage variation and 7 percent in Denmark. Torres et al. (2018) not only show that high-wage (low-wage) workers tend to work at high-wage (low-wage) firms but also present evidence in a second step on positive productivity-based matching between workers and firms. Recently, Lochner/Schulz (2022) showed that wage-based matching between workers and firms is much stronger than productivity-based matching and only wage-based sorting increased over time and thus contributes to rising wage inequality in Germany. We contribute to this literature in two ways, namely by providing insights on the life cycle dimension of assortative matching and using a novel way to measure assortative matching.

Second, this study also closely relates to previous empirical work on job mobility and its returns. We measure the development of assortative matching, which, in our framework, can only change due to job mobility across employers. Topel/Ward (1992) suggest that wage gains through job mobility account for a third of wage growth, at least at the beginning of the career. Likewise, Keith/McWilliams (1999) point towards the importance of returns to job mobility for young workers while the role of assortative matching in this process remains unclear. Building on a job ladder model with search frictions, a group of studies empirically assess the returns to job mobility. Moscarini/Postel-Vinay et al. (2018) analyze workers' movement up a job ladder, a commonly known ranking of jobs based on size, paid wage and productivity of firms. This job ladder can be climbed by workers through job mobility. The authors show that the pace of upward-moves is slower in recessions where the risk of falling down the job ladder into unemployment is especially high. Haltiwanger et al. (2018) separate job ladder movements, namely into a rank in terms of firm pay level and in terms of firm size. In their empirical analysis the authors find little evidence for movements towards larger firms, mostly due to the poaching activity by young, small firms. However, they find that job switchers move towards high-wage firms, especially in times of economic booms. Haltiwanger/Hyatt/McEntarfer (2018) also build on cyclical job ladders and examine what kind of workers move up the job ladder, a ranking of firms by productivity. They find that more often young and less-educated workers move up the (productivity) job ladder. Interestingly, the latter result somewhat contradicts assortative matching. The authors explain the upward-mobility of less-productive workers with a higher willingness to separate from their employer, especially during recessions. However, the authors also find evidence for assortative matching as the share of high-skilled workers at highly productive firms is higher than the share of low-skilled workers. Engbom (2022) provides insight on cross-country differences in life cycle earnings. He analyzes the relationship between labor market mobility and life cycle wage growth in a cross-country comparison. He finds that in labor markets that are characterized by high fluidity, life-cycle wage growth is more pronounced. Higher mobility encourages wage growth by allowing workers to move up the job ladder more quickly. Being in better jobs at larger, high-wage firms allows and incentivizes them to train more, while workers in labor markets that are characterized by less mobility anticipate their "stuckness" and thus train less. By evaluating whether workers and firms of similar quality are matched and seeing how this degree of matching differs over the life cycle, we also in a sense build on the structure of a job ladder since we rank firms by their quality. Our approach allows to assess the importance of assortative matching in the job ladder models.

Third, by assessing the importance of assortative matching and its development for cohort wage inequality over the life cycle, this study is related to previous work on the determinants of cohort wage inequality (Huggett/Ventura/Yaron, 2011; Magnac/Roux, 2021; Griffy, 2021). Bingley/Cappellari (2022) study the importance of firm and worker heterogeneity for life cycle wages and inequality in Italy. The authors do not use an AKM model but chose a life cycle wage model. Different shocks can shape life cycle wages and are either individual-, firm-, or match-specific. Further, they are able to distinguish between different career stages and blue and white collar workers. The authors find that worker-firm sorting can explain 40 percent of overall wage inequality while firm-specific factors explain 15 percent. For young workers, most of the wage inequality can be explained by firm-specific factors which are also more dominant for blue-collar than white-collar workers.

The paper is organized as follows. In chapter 2 the data set and most important variables for the empirical analysis are introduced. chapter 3 explains and discusses the AKM model, as well as the measurement of assortative worker-firm matching. We present our main results, mechanisms, robustness checks and the subsection on assortative matching and wage inequality in chapter 4 before we conclude in chapter 5.

2 Data and Variables

For the empirical analysis, we use the Integrated Employment Biographies (IEB, version V16.00.01-202012), an administrative data set containing information on episodes of employment, unemployment and participation in measures of active labor market policy for the universe of labor market participants in Germany. The data set includes day-precise employment episodes with information on average daily wages, employment duration and employment type (part- and full-time, regular and marginal employment). Additionally, the data set contains information about the individuals such as skill level, occupation, birth year, place of living and birth and nationality. The data further includes details about the establishments[3] in which individuals work, such as sector or region. This IEB version covers the years 1975-2020 for former West Germany and 1992-2020 for former East Germany.

We select the years 1995 until 2019 for our analysis of worker-firm matching. In doing so, we leave enough time after German reunification to ensure that East German employment records are accurately integrated into the IEB. To avoid any distortion due to the COVID-19 pandemic, we also exclude the year 2020. We restrict the sample to regular workers who are employed subject to social security contributions (other worker groups, such as apprentices and marginal employees, are therefore not included). We retain all employment spells that contain June, 30th of the respective year and thereby transform the spell data into a yearly panel with one observation per individual and year. In case of parallel employment spells, we choose episodes with longer establishment tenure. We impute wages that lie above the social security contribution limit (Dustmann/Ludsteck/Schönberg, 2009; Card/Heining/Kline, 2013), details can be found in section A1. We further restrict the sample to full-time workers since the IEB does not provide average daily working hours. We follow Card/Heining/Kline (2013) and Dauth et al. (2022) and select only men for our sample since the group of full-time working women is much more selective than is the case for men. Further, the sample is restricted to workers aged between 18 and 60. This sample is used to estimate the AKM model (chapter 3) and includes around 28 million workers and 3.9 million establishments.

In order to examine the degree of worker-firm matching over the life cycle, we count the jobs for each worker. We define a new job by a change in the establishment identifier. The reason we do not take changes within establishments into account is twofold: First, job changes within the establishment do not have to be reported by the employer and thus it is unclear how many within-establishment job changes could be identified. Second, we are interested in worker-firm matching and how it develops through mobility across firms. Therefore, we are explicitly interested in mobility from one plant to another. We focus on individuals that hold up to ten jobs in our sample period. Less than two percent of workers have a total of more than ten jobs (Table A1) and it can be argued that these workers show, on average, different characteristics than workers with fewer job changes. Even though we restrict the analysis period to the years 1995 to 2019, we use all available data of the IEB before 1995 to ensure that the job count in our sample period is correct and we do not miss any past job mobility. We undertake a robustness check where we exclude all workers whose age at the first job is above a certain age threshold to see whether any activity in the labor market that

[3] We use the terms plants, work sites and establishments interchangeably.

we potentially missed and thus a higher age at the observed labor market entry partly explains our results. In particular, this could be the case for East Germans whose labor market entry we are unable to track in the data prior to 1992 or for immigrants. We do not find evidence that our results are biased by these workers. Summary statistics for the observations we use in our analysis can be found in Table A2. The assessment of assortative matching relies on the identification of fixed effects of workers and establishments (chapter 3). We only work with observations for which both of these effects can be identified (which is the case for 89 percent of workers and 82 percent of establishments). Since both effects are time-invariant, we keep the first year of each worker-establishment combination. Therefore, the final sample is not weighted by job length.

3 Model and Identification

3.1 Wage Decomposition

In order to analyze assortative worker-firm matching, we follow the approach by Abowd/Kramarz/Margolis (1999) and assume that log daily wages of person i in year t can be decomposed into a time-invariant person fixed effect, a time-invariant firm fixed effect and an error term:

$$y_{it} = \alpha_i + \psi_{j(it)} + x'_{it}\beta + e_{it} \tag{1}$$

α_i represents the person fixed effect that captures individual time-invariant wage heterogeneity, e.g. due to personal characteristics like innate ability or work attitudes but also due to characteristics that may vary over time but are constant within the sample period like formal education. This individual-specific wage component can be transferred across employers. $\psi_{j(it)}$ is an establishment fixed effect that captures establishment heterogeneity in wages, i.e. an average wage premium or discount that affects each worker i at plant j. Wage premia could vary for instance due to rent-sharing, efficiency wages or strategic wage setting behavior. These AKM effects may hence capture worker or establishment productivity but also many other factors. We refer to the AKM effects as worker and establishment "quality", respectively. Vector x_{it} includes year dummies interacted with a dummy that indicates whether person i works in former East or West of Germany, as well as quadratic and cubic age terms fully interacted with skill level that control for skill-specific age-wage profiles. e_{it} is the error term which includes any worker-firm specific match effects and other random components. We estimate Equation 1 using all available years for a worker within our sample period which results in one fixed effect per worker and one per plant. The assumption that worker and establishment quality are constant over time might appear restrictive. However, recent evidence by Lachowska et al. (2023) shows that firm effects that are estimated repeatedly over one-year or two-year windows are remarkably similar.

The AKM model relies on several assumptions. Card/Heining/Kline (2013) showed the validity of the AKM model for the same German social security data that is also used in our study. Nonetheless, we replicate these tests and analyses. The AKM model (Equation 1) assumes an additive structure meaning that worker- and firm-specific wage components are separable. This indicates that all workers despite their skill level and other differences receive the same wage premium at establishment j[4]. The identification of the parameters of interest relies on another assumption, namely that the assignment of workers to firms is exogenous with respect to the error term e_{it}. Hence, job mobility is only allowed to depend on worker and firm heterogeneity, as well as time-varying observable characteristics (Abowd/McKinney/Schmutte, 2019). On the contrary, mobility based on the idiosyncratic match between worker and firm, which is a component of the error term, is not allowed. We follow Card/Heining/Kline (2013) and conduct an analysis of job movers in our sample to ensure that these assumptions are met in the data. Details can be found in section A3. The AKM establishment effect is identified from workers who move between firms. Lacking mobility of workers gives rise to a potential limited mobility bias (Abowd et al., 2004; Andrews et al., 2008) that could overstate the firm fixed effect and downward-bias the correlation between both fixed effects (Andrews et al., 2012; Bonhomme et al., 2023). We argue that limited mobility bias is not a large issue in our case. First, we work with a very long time period of 25 years (1995-2019), so even for small firms, there should be sufficient movers in our data. As Lachowska et al. (2023) point out, bias-correction in the form of Kline/Saggio/Sølvsten (2020) produces very similar results as the traditional AKM model, at least for long time intervals such as our period. Second, our preferred measure of assortative matching does not rely on second moments that are affected by limited mobility. Nonetheless, we conduct a robustness check inspired by Bonhomme/Lamadon/Manresa (2019) and re-estimate the AKM model for groups of establishments with similar pay structures instead of individual establishments. This means that each establishment (group) effect is identified by a larger number of moves.

[4] Some studies estimate this effect separately for worker groups, for example by gender, occupation, race or age (Card/Cardoso/Kline, 2016; Casarico/Lattanzio, 2024; Bruns, 2019; Kline/Saggio/Sølvsten, 2020; Gerard et al., 2021; Targa, 2023).

3.2 Assortative Matching

Assortative matching between workers and firms refers to the idea that workers of a specific quality tend to be employed at firms with a similar quality. Assortative matching therefore implies that high-quality workers tend to work at high-quality firms, while low-quality workers work at low-quality firms. We use two different approaches to quantify the degree of assortative matching. First, we follow Card/Heining/Kline (2013), Dauth et al. (2022) and Leknes/Rattsø/Stokke (2022) among others and define the degree of worker-firm matching as the correlation, ρ, between the estimated worker fixed effect ($\hat{\alpha}_i$) and the establishment fixed effect ($\hat{\psi}_{j(it)}$). A positive correlation ($\rho = Corr(\hat{\alpha}_i, \hat{\psi}_{j(it)}) > 0$) thus indicates positive assortative matching that arises when there is a complementarity of firm and worker quality. Since we are interested in the development of assortative matching over the life cycle, we calculate separate correlations between estimated worker and establishment quality for each job o ($\rho^o = Corr(\hat{\alpha}_{i(o)}, \hat{\psi}_{j(i(o)t)})$). This means that we compute the correlation between the estimated worker quality of all workers who are observed in job o and the estimated quality of the establishment that these workers are employed at in job o. The degree of correlation between estimated worker and establishment fixed effects can change over the life cycle for two reasons. First, the allocation of workers to establishments changes over the life cycle when workers move from one plant to another. Second, the underlying population changes over the life cycle as not all workers have the same number of jobs. As the number of workers decreases with the number of jobs, it is therefore possible that the correlation-based measure of assortative matching is subject to sample selection issues.

Second, we develop a novel measure of assortative matching. While the traditional approach relies on correlations that are computed on an aggregate of workers, our second measure is able to measure assortative matching for each worker-firm pair. To our knowledge, a similar measure has not been used previously. We rank all workers by their estimated person fixed effect ($\hat{\alpha}_i$) and assign workers to one of 100,000 equally large bins based on their rank. Each bin consists of 249 or 250 workers. Likewise, we assign each establishment quality estimate, $\hat{\psi}_j$, to one of 100,000 equally large bins consisting of 32 or 33 establishments. We define the rank of the bin that a worker's fixed effect is assigned to as $r_i = r^i(\hat{\alpha}_i)$. Similarly, the rank of the bin that an establishment's estimated quality is assigned to is given by $r_j = r^j(\hat{\psi}_j)$. Next, we compute the absolute distance between the rank of the worker and establishment bins for each worker i who is employed at establishment j and is in job o, $d^o_{ij(io)} = |r_i - r_j|$. For example, if a worker was assigned to bin number 100,000 (the bin with the highest-quality workers) and works at an establishment that was assigned the bin 80,000, the absolute difference between this worker's quality and the establishment's quality is 20,000. The smaller the (absolute) difference between a worker's and an establishment's rank, the more assortative is the match between worker and establishment, while a difference of zero can be interpreted as a perfectly assortative match.[5] Deviations from assortative matching can arise because workers are employed at establishments that are below their quality ($r_i - r_j > 0$) or above their quality ($r_i - r_j < 0$). By using the absolute value of the difference between the rank of the workers and the establishments, we ensure that any deviations from the benchmark of perfect assortative matching are considered and the positive and negative deviations do not cancel each other out.

One benefit of this measure is that it provides an estimate of assortative matching at worker level that potentially changes whenever a workers moves to a new establishment. Importantly, this allows us to address the concern that applies to the correlation-based measure, namely that changes in the measured degree of assortative matching across job numbers may reflect changes in the composition of workers and establishments rather than genuine changes in assortative matching. To asses how the degree of assortative matching, based on our distance measure, changes with job mobility, we estimate the following regression model:

$$d^o_{ij(io)} = \sum_{p=2}^{10} + \beta^1_o I(o = p) + \gamma^1_i + \beta^1 \mathbf{x}^1_{io} + e^1_{io} \tag{2}$$

Specifically, we regress the absolute distance between the ranks of the estimated worker and establishment effects, $d^o_{ij(io)}$, on an indicator that shows the job number o that worker i is in. We also include worker fixed effects, γ^1_i, to control for changes in the composition of workers over the number of jobs, while vector $\mathbf{x}^1_{io}$ includes a number of control variables that we use in some specifications, such as skill level, region of the workplace, 2-digit KldB occupation, 2-digit industry and establishment size. e^1_{io} represents a random error term.

Since a worker's estimated quality, and hence its rank in the worker quality distribution, is fixed, changes in the distance variable can only come through changes in the rank of the establishment's estimated quality. To illustrate whether the change in the distance is due to switching to higher- or lower-quality establishments, we also estimate a similar model to the one in Equation 2, where we use the estimated establishment fixed effects as the dependent variable:

$$\hat{\psi}_{j(io)} = \sum_{p=2}^{10} \beta^2_o I(o = p) + \gamma^2_i + \beta^2 \mathbf{x}^2_{io} + e^2_{j(io)} \tag{3}$$

[5] We use the rank-difference instead of the difference between the estimated fixed effects to mitigate the influence of outliers but conduct a robustness check in which we use the raw difference.

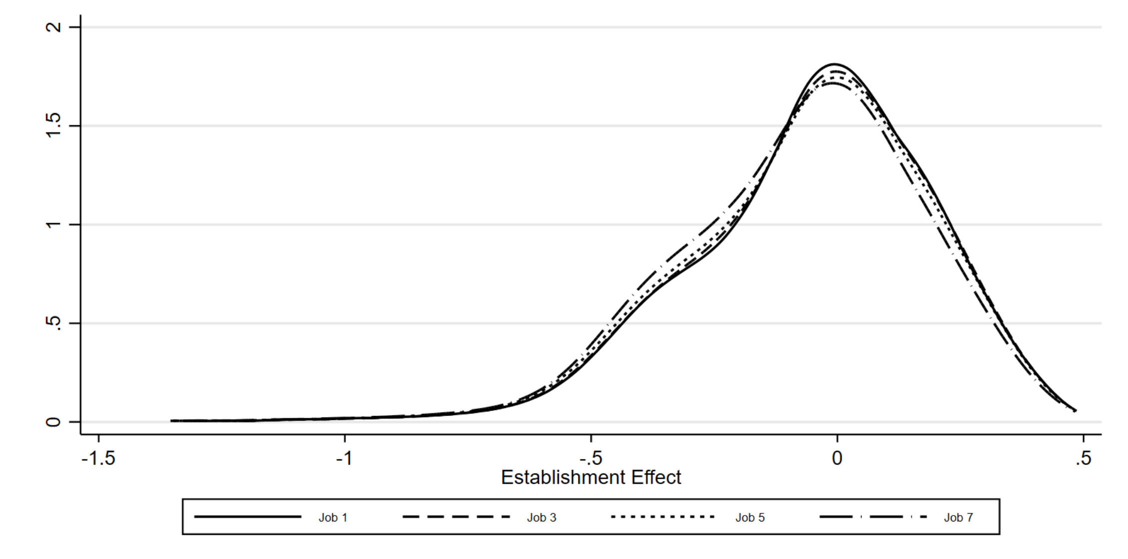
4 Results

4.1 Identifying Worker and Firm Quality

In a first step, we estimate the AKM model (Equation 1) to retrieve person and establishment fixed effects that are needed to calculate the degree of assortative matching. Table A3 shows the mean estimated worker and establishment fixed effects, separately by job number for our analysis sample. The correlation between the estimated worker and establishment fixed effects across all jobs is 0.35. This value is of a similar magnitude as the findings of Card/Heining/Kline (2013) (for the period 2002-2009) and Lochner/Schulz (2022) (period 1998-2008) who also use IEB data.

It is possible that job mobility is selective in the sense that specific workers work at specific kinds of plants at different stages of their career. Moreover, the total number of jobs a worker has during their career may be related to (un)observable characteristics. This could impact our worker-plant matching measures. To see whether plants and workers systematically differ between jobs in terms of quality, Figure 2 and Figure 3 show the distribution of estimated worker and establishment effects. Since we are interested in the development of the degree of assortative matching over the career, we plot separate distributions for each job number (i.e. based on all worker-plant pairs for workers in their first job, second job, third job, etc.). We do not find strong evidence that establishment effects are systematically different across job numbers. Looking at the distribution of $\hat{\psi}_{j(it)}$, only the group of establishments at which workers are employed in later jobs, is shifted to the left, which indicates a higher fraction of lower-quality plants. Most importantly, no differences are apparent for the other job numbers. Turning to the distribution of $\hat{\alpha}_i$, there are slightly fewer workers in the later jobs with higher quality compared to earlier jobs and slightly more mass of high-quality workers in the first job. Otherwise there are no visible differences across job numbers. This descriptive evidence suggests that there are no large compositional changes across jobs with respect to worker and plant quality. Including worker fixed effects in our regression framework helps to mitigate any potential composition differences.

Figure 2: Distribution of Estimated Establishment Effects by Job Number



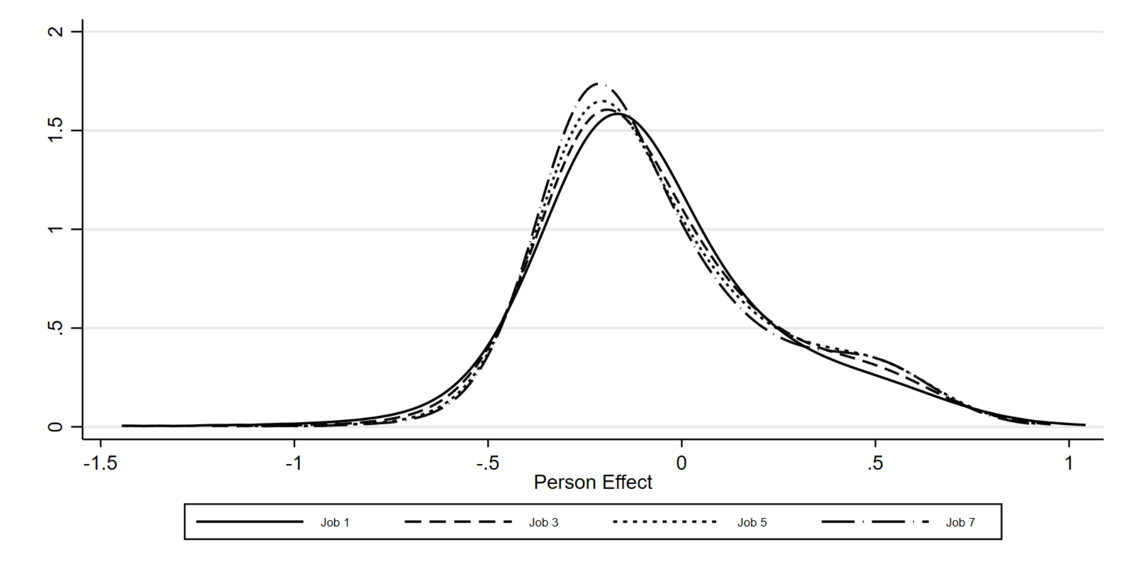
Notes: The figure shows the distribution of estimated AKM establishment fixed effects for workers in their 1st, 3rd, 5th and 7th job. Establishment fixed effects are obtained from the estimation of Equation 1.
Source: IEB, own calculations. ©IAB

4.2 Assortative Matching over the Career

Correlation between Fixed Effects

In a next step, we compute the degree of assortative matching for all observations in different jobs over the career. Figure 4 shows the correlation between the estimated worker and establishment fixed effects by job number. The first result is that we find clear evidence for assortative matching in our data, as shown by the positive correlation between worker and plant fixed effects in all jobs. Further, we find that the degree of matching between workers and plants tends to increase over the career. Between the first and the sixth job the correlation increases by 37 percent (from 0.2907 to 0.3996) before it slowly decreases. These baseline results show that workers and establishments are matched assortatively starting from the very beginning of the career. With each job move, this tendency increases. This suggests that mobility is, on average, accompanied by an improvement in the degree of assortative matching which is most explicit between the first and fifth job of a worker. One concern is that the changes in the degree of correlation are due to changes in the composition of workers and establishments as seen in Figure 2 and Figure 3. To address this concern, we residualize the estimated worker and plant fixed effects by regressing them on a set of worker- and establishment-specific control variables (section A5) and then compute the correlation of the residuals. As can be seen in Figure A3, the correlation between residualized worker and plant fixed effects is still increasing.

Figure 3: Distribution of Estimated Person Effects by Job Number



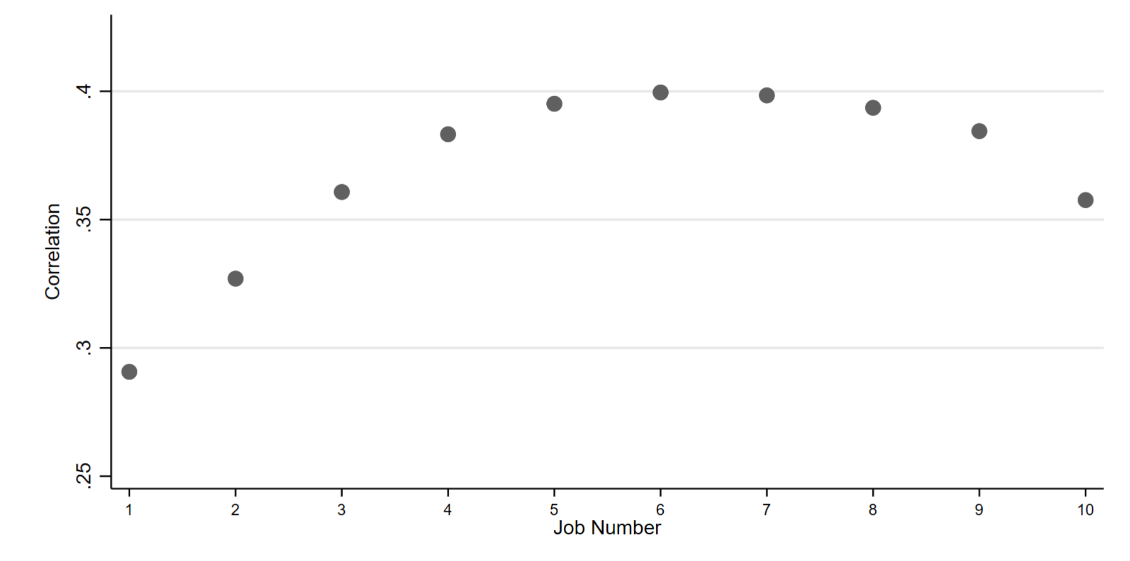
Notes: The figure shows the distribution of estimated AKM person fixed effects for the 1st, 3rd, 5th and 7th job. Person fixed effects are obtained from the estimation of Equation 1.
Source: IEB, own calculations. ©IAB

Distance between Worker and Establishment Quality

Figure 5 shows the distribution of the distance between worker and firm quality for selected jobs. Importantly, this figure shows the actual and not the absolute distance. This allows to see whether workers are, on average, mismatched because the firm is of higher or lower quality than the workers. In their first job, more workers are employed at firms that have a higher quality than themselves. In jobs three, five and seven there are fewer of these mismatches and more worker-firm pairs that display a distance between qualities around zero.

Figure 6 shows the mean absolute distance between worker and establishment quality separately for each job. Over the career, the average distance between worker and establishment quality is falling. While the average distance is 29,178 in the first job, it decreases to 25,996 in the ninth job. This means that workers and plants are, on average, 29,000 bins apart at the beginning of the career and only 26,000 bins later on, which corresponds to a decrease by 11 percent. We conclude that our alternative measure of assortative matching captures a similar pattern over the career as the traditional approach of using the correlation. Table 1 shows the results from estimating Equation 2. Column (1) shows that, on average, the distance between the rank of the estimated person and establishment fixed effects falls by about 475 bins whenever a person moves to a different employer, indicating that job mobility is associated with increases in assortative matching. In column (2), we focus on the development with job mobility. Compared to the first job, the

Figure 4: Assortative Matching over the Career

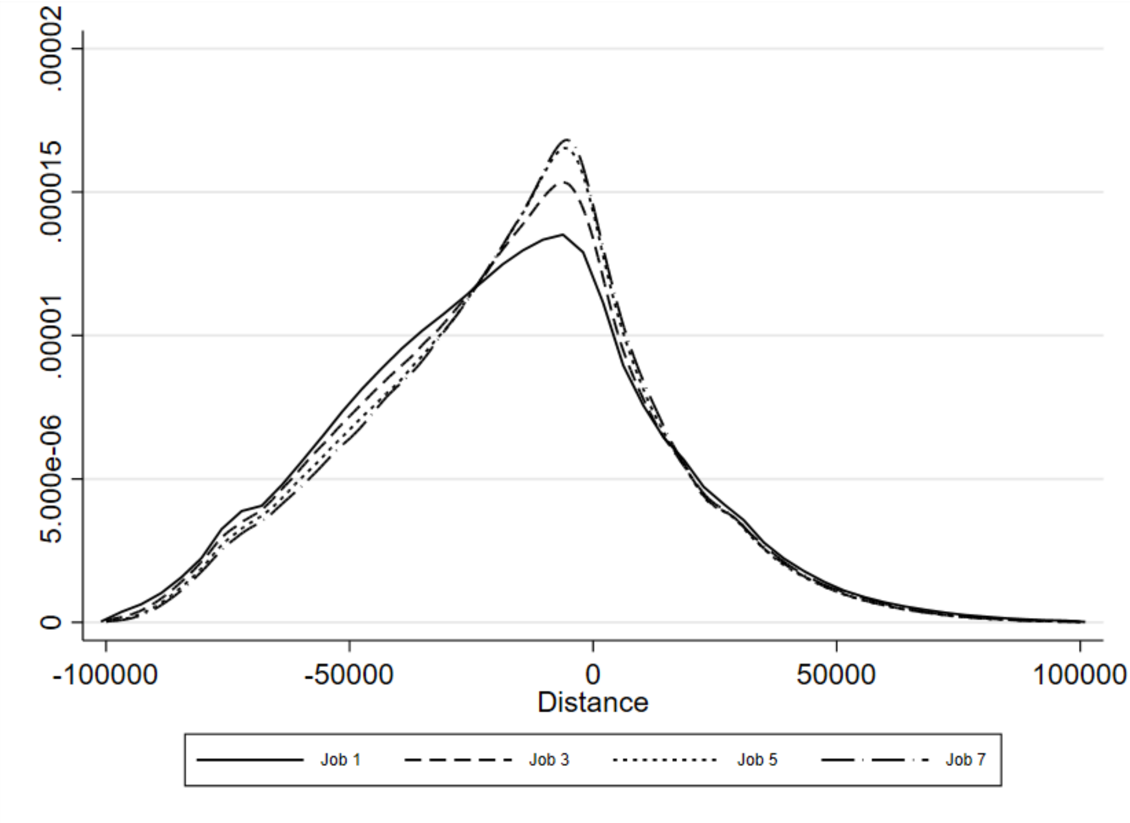


Notes: The figure shows the correlation between the estimated AKM establishment and person fixed effects by job number. Both effects are obtained from the estimation of Equation 1.
Source: IEB, own calculations. ©IAB

distance between worker and plant quality falls steadily up to the ninth job. In order to control for changes in the composition of workers in each job number, we add worker fixed effects (column 3), and control variables such as skill level, region (East/West), occupation, sector and establishment size (column 4). Controlling for unobserved heterogeneity shows that the reduction in the distance between worker and plant quality does not start immediately, but rather with the fourth employer. The second and third job are associated with an increase in the distance compared to the first job, and thus a less assortative match between workers and establishments. When additionally controlling for observable worker, job and work site characteristics, we still find a widening of the gap in the second job. However, this is followed by a convergence of worker and establishment quality for the remaining jobs and thus an increase in the degree of assortative matching.

Changes in the degree of assortative matching are always due to a move towards an employer of a different quality than the previous employer since the estimated person effects are constant throughout the employment course. To study the mobility between establishments, we regress the estimated establishment effects on the job number (Equation 3). Column (1) of Table 2 shows that, on average, job mobility is associated with a decrease in establishment quality. Column (2) shows a negative pattern over the career meaning that, on average, workers move towards plants with lower estimated AKM effects. Again, this could be driven by a changing composition of workers between job numbers. When controlling for worker unobserved heterogeneity in column (3), we find that, on average, all jobs until the seventh job are associated with a higher plant quality than the

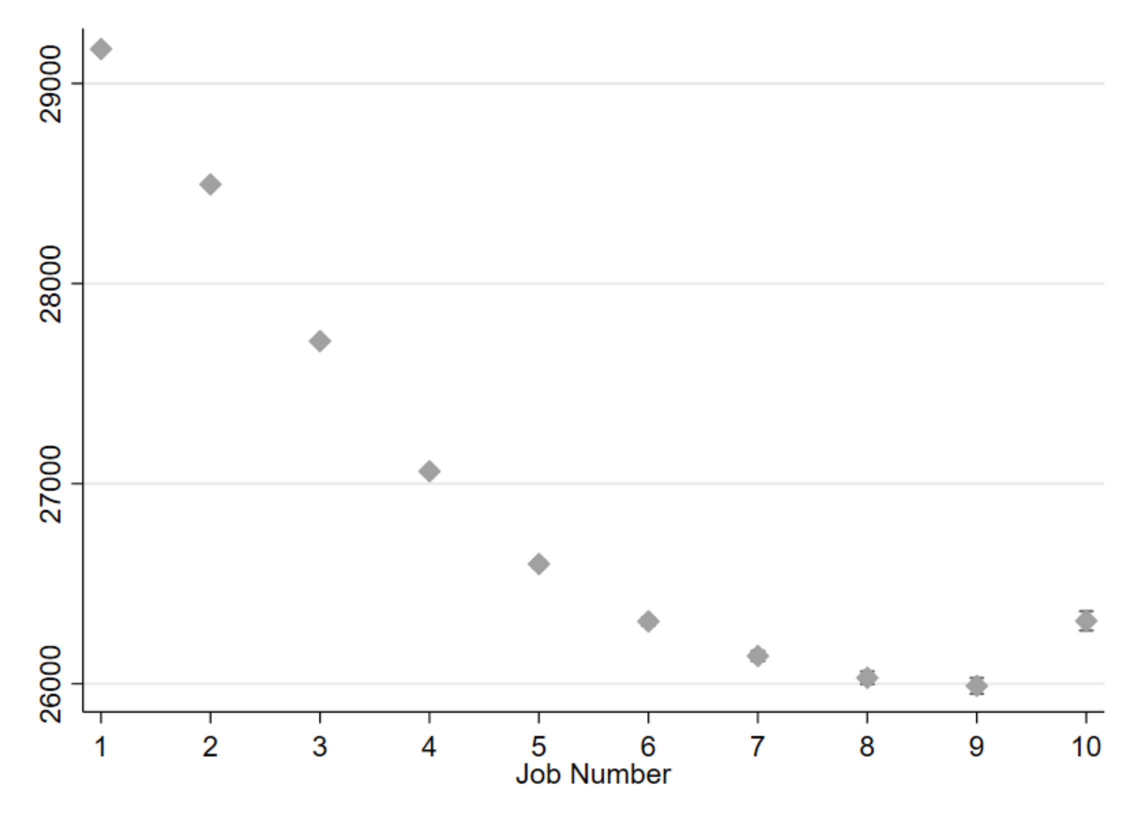
Figure 5: Distance between Worker and Establishment Quality



Notes: The figure shows the distance between the estimated worker and establishment quality for the 1st, 3rd, 5th and 7th job. The distance between worker and establishment quality is based on 100,000 worker and establishment bins. The bins are based on estimated AKM person and establishment fixed effect obtained from Equation 1. A negative (positive) distance implies that, on average, the establishments estimated quality is higher (lower) than the workers. A distance equal to zero is a perfectly assortative match.
Source: IEB, own calculations. ©IAB

first job but only jobs two and three are associated with an improvement compared to the previous job. Adding control variables in column (4) gives similar results. While Table 1 revealed less assortative matches at the beginning of the career after controlling for unobserved heterogeneity, Table 2 shows that those jobs take place, on average, at higher-quality establishments. Vice versa, later jobs are at establishments with lower quality but result in more assortative matches. This implies that the improvement in assortative matching cannot mainly be driven by high-quality workers since moving to establishments with a higher (lower) fixed effect should result in a more (less) assortative match for them.

Figure 6: Mean Absolute Distance between Worker and Establishment Quality over the Career



Notes: The figure shows the mean absolute distance between the estimated worker and establishment quality separately by job number. The distance between the estimated worker and establishment quality is based on 100,000 worker and establishment bins. The bins are based on estimated AKM person and establishment fixed effect obtained from Equation 1. Standard errors are clustered at the worker level.
Source: IEB, own calculations. ©IAB

4.3 Mechanisms

Worker Quality

In order to explore the mechanisms that drive the increase in assortative matching with job mobility, this subsection examines whether our baseline results differ between high- or low-quality workers. To this end, we split all workers into four equally large groups based on the quartiles of their estimated AKM worker effect. We then estimate Equation 2 and Equation 3, separately for the 25 percent of workers with the lowest quality and the 25 percent with the highest quality. Table 3 shows the results. The quarter of workers with the smallest estimated person fixed effects work, on average, in less assortative matches and lower-quality plants in their first job, compared to the quarter of workers with the highest estimated effects. This is due to the fact that low-quality workers start in establishments that have a higher quality rank than their own (mean distance of -39849 and median

Table 1: Assortative Matching over the Career: Distance Measure

	(1)	(2)	(3)	(4)
	Dependent Variable: Absolute Difference			
Job Change	-475.3***			
	(1.609)			
Job 2		-676.5***	476.5***	192.7***
		(6.955)	(7.401)	(6.919)
Job 3		-1459.9***	421.8***	-13.47
		(8.051)	(8.898)	(8.406)
Job 4		-2110.3***	-107.6***	-451.6***
		(9.078)	(10.27)	(9.709)
Job 5		-2573.8***	-805.2***	-951.9***
		(10.37)	(11.85)	(11.15)
Job 6		-2860.9***	-1560.8***	-1482.2***
		(12.07)	(13.77)	(12.89)
Job 7		-3033.6***	-2371.1***	-2045.9***
		(14.32)	(16.20)	(15.07)
Job 8		-3142.4***	-3245.6***	-2648.3***
		(17.25)	(19.32)	(17.86)
Job 9		-3183.0***	-4196.2***	-3311.2***
		(21.13)	(23.42)	(21.51)
Job 10		-2857.9***	-5240.6***	-4036.1***
		(25.25)	(28.53)	(26.13)
Constant	29354.8***	29172.6***	28092.7***	22057.1***
	(6.074)	(5.903)	(6.205)	(404.9)
Worker FE	no	no	yes	yes
Controls	no	no	no	yes
N	62,709,423	62,709,423	62,709,423	62,709,423
R^2	0.002	0.002	0.003	0.189

Notes: The table shows the results from estimating different specifications of Equation2. The dependent variable is the distance between worker and establishment quality. It is based on 100,000 person and establishment quality bins that were derived from the distributions of the estimated worker and establishment AKM fixed effects. Controls include skill level, region (East/West), 2-digit occupation and sector and plant size. Standard errors in parentheses, clustered on worker level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Source: IEB, own calculations. ©IAB

distance of -38191). The matching pattern differs between the two groups, too. Low-quality workers can be found in less assortative matches up until the third job, before the distance between worker and plant quality starts to decrease (column 1). At the same time, for high-quality workers, the distance between worker and establishment quality decreases right at the beginning of the employment course (column 3) before increasing again with the fifth job. To sum up, the distinction between high- and low-type workers indicates that our finding in Table 1 that the reduction of the distance only starts from the forth job is driven by low-quality workers.

The results for high quality workers are compatible with job ladder models like the wage posting models of Burdett/Mortensen (1998) and Christensen et al. (2005). Workers search on the job and accept any job that offers a higher wage than the current job. Within the AKM framework, this requires that the new job is at a plant with a higher fixed effect. Low-quality

Table 2: Movement along Establishment Quality

	(1)	(2)	(3)	(4)
	Dependent Variable: Establishment Quality			
Job Change	-0.00437***			
	(0.0000203)			
Job 2		-0.00113***	0.0186***	0.0112***
		(0.0000770)	(0.0000838)	(0.0000738)
Job 3		-0.000831***	0.0247***	0.0128***
		(0.0000910)	(0.000101)	(0.0000898)
Job 4		-0.00364***	0.0215***	0.00884***
		(0.000105)	(0.000116)	(0.000104)
Job 5		-0.00888***	0.0141***	0.00248***
		(0.000122)	(0.000134)	(0.000119)
Job 6		-0.0160***	0.00489***	-0.00515***
		(0.000144)	(0.000155)	(0.000137)
Job 7		-0.0245***	-0.00561***	-0.0135***
		(0.000172)	(0.000182)	(0.000160)
Job 8		-0.0342***	-0.0175***	-0.0228***
		(0.000209)	(0.000215)	(0.000189)
Job 9		-0.0440***	-0.0305***	-0.0327***
		(0.000256)	(0.000259)	(0.000226)
Job 10		-0.0497***	-0.0457***	-0.0445***
		(0.000304)	(0.000314)	(0.000273)
Constant	-0.0451***	-0.0537***	-0.0708***	-0.209***
	(0.0000724)	(0.0000671)	(0.0000706)	(0.00460)
Worker FE	no	no	yes	yes
Controls	no	no	no	yes
N	62,709,423	62,709,423	62,709,423	62,709,423
R^2	0.001	0.002	0.005	0.267

Notes: The table shows the results from estimating different specifications of Equation 3. The dependent variable is establishment quality, measured as the estimated AKM establishment fixed effect. Controls include skill level, region (East/West), 2-digit occupation and sector and plant size. Standard errors in parentheses, clustered on worker level. $^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$.
Source: IEB, own calculations. ©IAB

workers are also likely to try to climb the job ladder. This appears to work out for the first few moves but not later in the career. This can be explained by a model where worker ability is private information and revealed only after a period of employment as in Gibbons/Katz (1991) and Laing (1994). Firms will separate from bad matches and future employers learn from those separations which implies that with each job move, low-quality workers find it increasingly difficult to match with high-quality employers. Columns (2) and (4) support this explanation. Low-quality workers (column 2) move to higher-quality plants in the second, third and forth job, after that they move to establishments that have a lower quality than their first employer. This explains why the distance between worker and plant quality widens at the beginning of the career for these workers. For high-quality workers (column 4) we find that they move towards establishments with a higher quality than the previous work site up until the sixth job which results in increasingly more assortative matches.

Table 3: Assortative Matching and Establishment Quality by Worker Quality

	(1)	(2)	(3)	(4)
	Low-AKM		High-AKM	
	Abs. Distance	Est. Quality	Abs. Distance	Est. Quality
Job 2	1480.7***	0.0151***	-1269.4***	0.0383***
	(16.50)	(0.000160)	(13.69)	(0.000177)
Job 3	1496.0***	0.0150***	-1848.3***	0.0608***
	(19.66)	(0.000191)	(16.26)	(0.000211)
Job 4	419.0***	0.00502***	-1927.0***	0.0727***
	(22.69)	(0.000220)	(18.28)	(0.000237)
Job 5	-1041.8***	-0.00844***	-1697.7***	0.0783***
	(26.16)	(0.000254)	(20.57)	(0.000266)
Job 6	-2618.5***	-0.0222***	-1314.4***	0.0799***
	(30.32)	(0.000294)	(23.55)	(0.000303)
Job 7	-4231.5***	-0.0359***	-827.7***	0.0790***
	(35.51)	(0.000343)	(27.61)	(0.000353)
Job 8	-5951.8***	-0.0502***	-218.9***	0.0760***
	(41.97)	(0.000405)	(33.36)	(0.000423)
Job 9	-7726.3***	-0.0644***	405.4***	0.0718***
	(50.42)	(0.000484)	(41.43)	(0.000519)
Job 10	-9660.2***	-0.0805***	1254.2***	0.0649***
	(60.87)	(0.000583)	(52.79)	(0.000649)
Constant	38360.7***	-0.178***	17714.5***	0.0203***
	(13.32)	(0.000129)	(11.79)	(0.000154)
Worker FE	yes	yes	yes	yes
Controls	no	no	no	no
N	18,165,562	18,165,562	13,588,981	13,588,981
R^2	0.008	0.007	0.004	0.022

Notes: The table shows the results from estimating different specifications of Equation 2 and Equation 3. The dependent variable is either the distance between worker and establishment quality (columns 1 and 3) or establishment quality, measured as the estimated AKM establishment fixed effect (columns 2 and 4). Models are estimated separately for workers whose estimated worker fixed effects falls into the bottom quartile (Low-AKM) or the top quartile (high-AKM) of the estimated worker fixed effects distribution. Controls include skill level, region (East/West), 2-digit occupation and sector and plant size. Standard errors in parentheses, clustered at the worker level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Source: IEB, own calculations. ©IAB

Voluntary and Involuntary Mobility

The finding of an increasing matching pattern for low-quality workers can be rationalized by the worker quality being private information that is revealed to future employers due to involuntary separations. While the data does not give reasons for the termination of employment spells, we know whether workers had an interruption between jobs. We use this information as a proxy to distinguish voluntary and involuntary moves by assuming that job switches without interruption were voluntary, whereas non-consecutive employment spells are considered the result of an involuntary separation. Due to the data structure, an involuntary move is defined as a job that covers June 30th of year t but the person was not employed on June 30th in $t-1$. In between, workers may have been unemployed, out of the labor force, participating in measures of active labor market policy or working in marginal or part-time jobs.

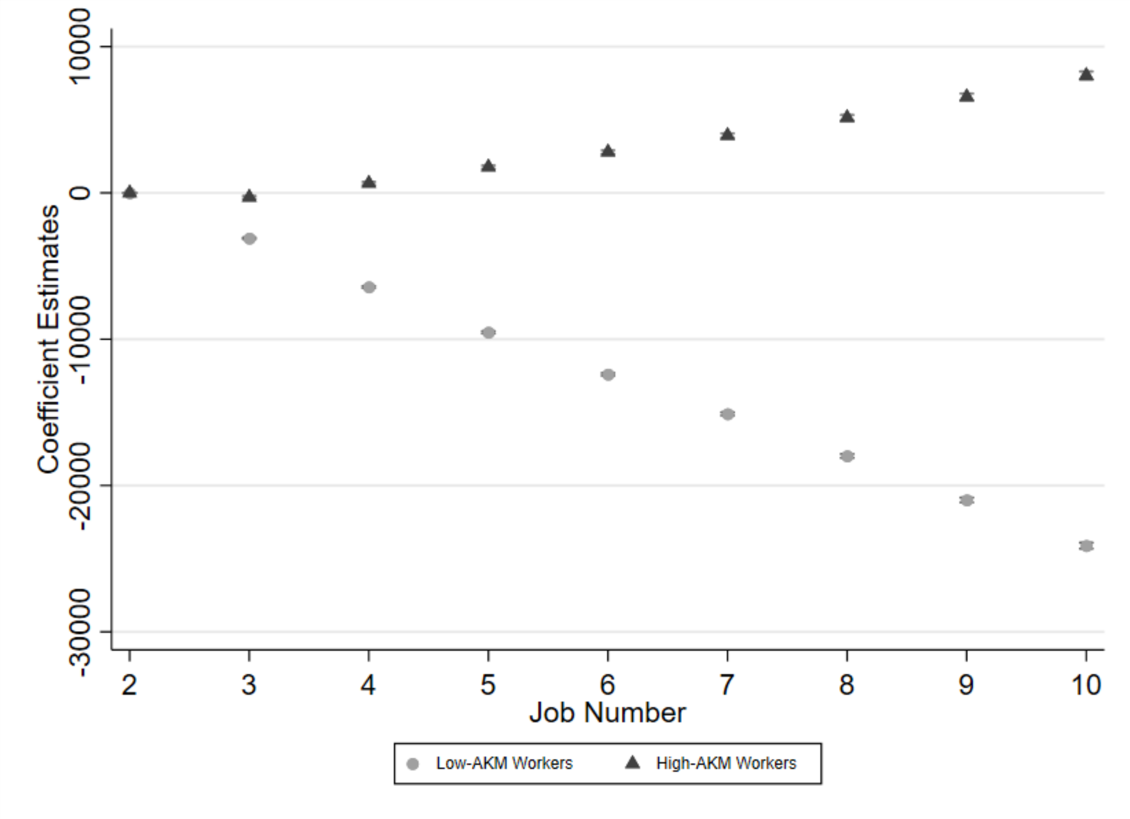
We then regress the distance between worker and establishment quality on job numbers interacted with indicators for whether a job separation was involuntary. Estimation of this model is then done separately for low-quality and high-quality workers, respectively. We also estimate a similar model using the estimated establishment quality as the dependent variable. In both models, worker fixed effects are included. If experiencing an involuntary separation is perceived by future employers as an indicator of lower worker quality, we would expect that an involuntary move is associated with a reduction in plant quality (relative to a voluntary move) for both low-quality and high-quality workers. By contrast, we would expect that for high-quality workers involuntary moves should be associated with an increase in the distance between worker and plant quality, whereas for low-quality workers the distance should fall. Figure 7 shows the coefficient estimates of the interaction between job number and the indicator for an involuntary move separately for low- and high-quality workers in a regression of distance, while Figure 8 shows the corresponding coefficients on establishment quality. Consistent with our expectations, it can be seen that an involuntary move reduces the distance between worker and establishment quality for low-quality workers (relative to a voluntary move), while the distance tends to increase with an involuntary move for high-quality workers. In both cases, the absolute size of the effect increases with the job number. For both types of workers, we find that, for most job numbers, involuntary moves are associated with a reduction in plant quality. For high-type workers, future employers might misinterpret an involuntary separation as a signal for low quality.

4.4 Robustness

Limited Mobility Bias

Recent evidence by Bonhomme et al. (2023) has highlighted the need to address limited mobility bias when working with estimated worker and firm fixed effects from an AKM wage decomposition, especially with second moments. To respond to these findings, we conduct a robustness check inspired by Bonhomme/Lamadon/Manresa (2019); Bonhomme et al. (2023) and estimate grouped plant fixed effects to increase mobility in our sample. By working with groups of establishments instead of individual ones, we aim at reducing the possibility of small establishments with low mobility to bias results. Using a k-means cluster analysis, we group establishments into $k = 100$ groups. We follow Dauth et al. (2022) and measure the distribution of wages in each establishment by $m = 40$ wage percentiles. We then re-estimate Equation 1 but use the obtained establishment groups instead of individual establishments. For each worker-plant pair, we then compute how close/far apart a worker's position in the distribution of the estimated worker fixed effects is to the position of the plant (plant group) in the corresponding plant fixed effects distribution. In

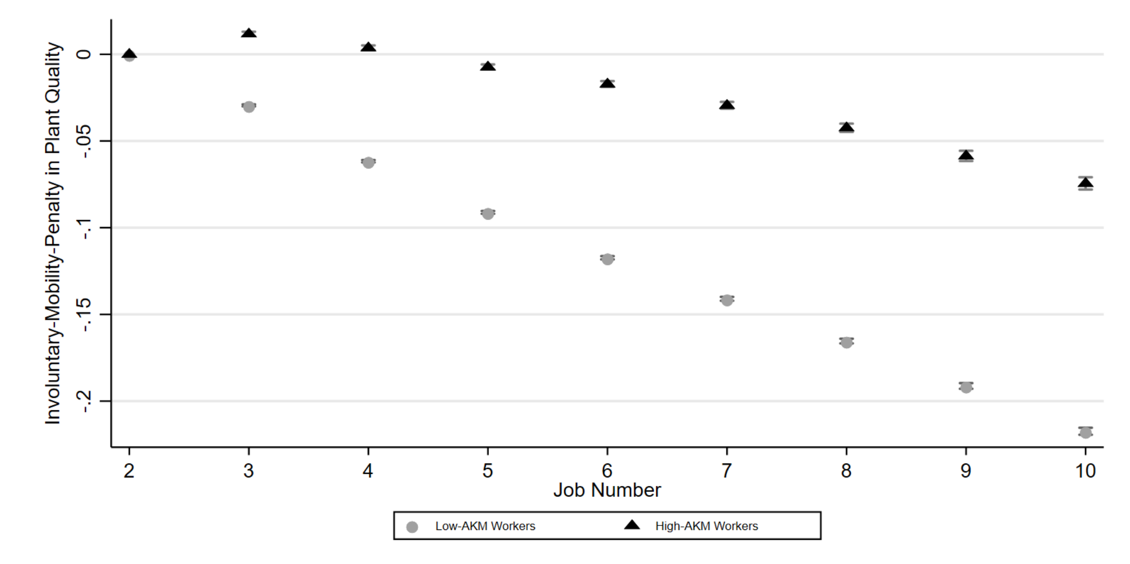
Figure 7: Involuntary Mobility: Assortative Matching



Notes: The figure shows the estimated coefficients of regressing the distance between the estimated worker and establishment quality on an indicator variable for a worker's job number interacted with a dummy that shows whether the separation from the previous employer was involuntary. First job observations are excluded since the first job cannot be defined as voluntary or involuntary. The estimated coefficients can be interpreted as the average difference in the change in the average distance between a person's second job and job o for workers who either left their previous job voluntarily or involuntarily. The results are shown separately for workers whose estimated AKM person effect fall into the top quarter (triangles) or bottom quarter (circles) of the AKM worker effect distribution. Standard errors are clustered at worker level.
Source: IEB, own calculations. ©IAB

contrast to the distance that was introduced in section chapter 3, we have to account for the fact that the number of worker bins differs from the number of plant group bins. While there are 100 establishment clusters (k_j) that all consist of a different number of establishments, we still rank workers by their estimated fixed effect and assign them to one of 100,000 equally large bins (r_i). Workers that belong to the group with the lowest (highest) estimated worker fixed effects are considered to have assortative matches with plants within the cluster with the lowest (highest) estimated plant group fixed effect. However, we also consider differences in worker quality within bins. Worker bins can be seen as intervals where the worker fixed effects are ranked by magnitude. We assume that the worker in the middle of each interval is perfectly matched (adjusted distance=0) with plants in the corresponding cluster. Depending on a worker's position on the interval, a match with a

Figure 8: Involuntary Mobility: Establishment Quality



Notes: The figure shows the estimated coefficients of regressing the establishment quality measured as the estimated AKM establishment fixed effect, on an indicator variable for a worker's job number interacted with a dummy that shows whether the separation from the previous employer was involuntary. First job observations are excluded since the first job cannot be defined as voluntary or involuntary. The estimated coefficients can be interpreted as the average difference in the change in average establishment quality between a person's second job and job o for workers who either left their previous job voluntarily or involuntarily. The results are shown separately for workers whose estimated AKM person effect fall into the top quarter (triangles) or bottom quarter (circles) of the AKM worker effect distribution. Standard errors are clustered at worker level.
Source: IEB, own calculations. ©IAB

plant in another cluster could result in a smaller distance and thus a more assortative match. We calculate the adjusted distance measure, $\tilde{d}^{o}_{ij(io)}$, as

$$\tilde{d}^{o}_{ij(io)} = r_i - k_{j,it} + [(k_{j,it} + (k_{j,it} - 1)) \times 5 - k_{j,it}] \quad (1)$$

Table A4 shows the results for this exercise. Most important, after increasing mobility between establishments, it can still be seen that the distance between worker and establishment quality decreases over the career once we control for unobserved heterogeneity.

Observation Period

In our sample we include workers that appear in the IEB between 1995 and 2019. Naturally, this means that we observe some workers longer than others and for some of them only the very beginning or end of their employment course. This could have implications for the AKM estimation in Equation 1 and thus our matching pattern results. In this robustness check, we re-estimate the regression of our distance measure on job numbers (Equation 2) for a sub-sample of workers for who we observe the labor market entry, as well as at least the 18 subsequent years. This means that there are only workers whose biographies are not truncated before they appear in our data set and we therefore do not leave out an important part of their employment history towards the end of our sample period. Arguably, the first 18 years of a worker's career should capture job mobility which is known to be more prominent when workers are young. Applying this restriction results in 45 percent of all workers being included in this exercise. Table A5 shows the results of regressing the distance between worker and plant quality on the job number for this sample. We find similar matching patterns as in our main results. Job mobility is associated with a reduction in the distance between worker and establishment quality over the career. This result holds when controlling for unobserved worker characteristics and worker, plant and job controls. We conclude that our main results do not depend on including workers who are observed only for a limited number of years.

Further Robustness Checks

We conduct a series of further robustness checks. First, one may worry that the job number is mismeasured for workers who have accumulated labor market experience before entering the administrative data. This may apply in particular to workers who entered before 1975, East Germans, and immigrants. In various checks, we drop workers who entered the data late considering their educational degree, East Germans in 1992-2000, and workers with foreign nationality. Each of those checks shows that those groups have not been driving our results. In a final robustness check, we use the raw difference between worker and establishment estimated AKM effects instead of binning the effects first, which yields very similar results. Details on those further checks can be found in section A6.

4.5 Assortative Matching and Wage Inequality

This section addresses the question to what extent the increasing worker-firm matching with each new job contributes to the increasing wage inequality over the life cycle documented in Figure 1. We assess the importance of assortative matching by constructing counterfactual wage inequality profiles that would be predicted had the degree of assortative matching developed differently. Keeping all elements of the AKM framework of Equation 1 constant, an increase in the degree of assortative matching increases wage inequality. This relationship can be shown formally:

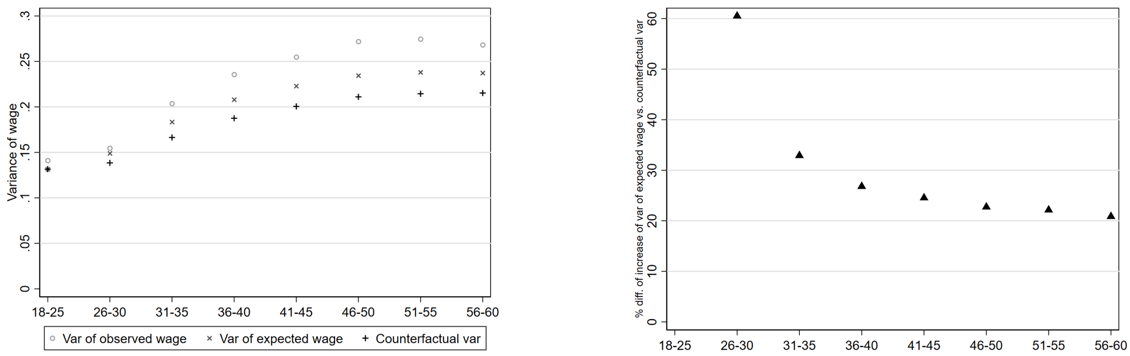
$$\begin{aligned} var\left[E(lnW)\right] =& var(\alpha_i) + var(\psi_{j(it)}) + var(x_{it}) + \\ & 2cov(\alpha_i, \psi_{j(it)}) + 2cov(\alpha_i, x_{it}) + 2cov(\psi_{j(it)}, x_{it}) \end{aligned} \tag{2}$$

Conditional on worker quality, α_i, plant quality, $\psi_{j(it)}$ and observable characteristics, x_{it}, wage inequality increases with the degree of assortative matching, as captured by the covariance between worker and establishment fixed effects.

To analyze to what extent the increase in the degree of assortative matching increases wage inequality, we perform a counterfactual exercise. More specifically, we compare the variances of observed wages, expected wages, and a counterfactual variance of expected wages. The counterfactual variance of wages is constructed by fixing

$cov(\alpha_i, \psi_{j(it)})$ at the initial level of assortative matching. We define the initial level of assortative matching as the average degree of assortative matching of workers aged 18 to 25. Figure 9a shows the three variances for different age groups. It can be seen that the variance of observed wages increases with age up until the age of 55. The variance of expected wages follows a flatter pattern but is also increasing with age. The difference between the variance of expected wages and the counterfactual variance reflects the part of the variance of expected wages that stems from assortative matching. Figure 9b illustrates how much this difference contributes to the increase of the variance of expected wages with age. Comparing age groups 18-25 and 26-30, the variance of expected wages increases only moderately and the counterfactual variance even less, which means that the difference between the two accounts for a quite large share of this small increase. In the following age groups, inequality of expected wages increases more substantially and assortative matching accounts for 20-30 percent of this increase. The contribution of assortative matching is of similar magnitude as the difference of the variance of expected and observed wages, i.e., the contribution of unobserved, time varying characteristics. This result indicates that the development of assortative matching with job mobility contributes significantly to the increase of wage inequality over the life cycle within cohorts.

Figure 9: Counterfactual Wage Inequality



(a) Wage Inequality over Life Cycle **(b) Difference Expected and Counterfactual**

Notes: Figure (a) shows the variance of observed wages, expected wages and a counterfactual variance of expected wages for different age groups. In the counterfactual variance, the covariance of estimated worker and establishment fixed effects is fixed at the level of the covariance when workers are 18-25 years old. Figure (b) shows the difference between the variance of wages of the expected wages and the counterfactual variance of wages. The difference can be interpreted as the part of the increase in wage inequality that stems from assortative matching.
Source: IEB, own calculations.©IAB

5 Conclusion

We analyze the development of assortative worker-firm matching with job mobility. Based on a rich administrative data covering the universe of German labor market participants from 1995 until 2019, we first estimate an AKM wage decomposition. We then use two measures to capture assortative matching. First, we compute the correlation between both estimated AKM establishment and worker fixed effects. We then compare the correlations along different stages of the career to see whether the degree of assortative matching increases. Second, we develop a new measure to quantify assortative matching for each individual worker-establishment pair. This new measure allows us to analyze assortative matching in a regression framework and control for (un)observable heterogeneity.

We find evidence for assortative matching in the data with an overall correlation of worker and plant effects of 0.35. Most importantly, we document an increase in assortative worker-firm matching with each job move. The correlation increases from 0.29 in the first job to 0.40 in the sixth job. Building on the distance between worker and establishment quality as the measure of assortative matching, we corroborate the finding that, on average, job mobility is associated with an increase in the degree of assortative matching. When controlling for (un)observed worker characteristics, jobs at the beginning of the employment course are associated with an increase in the distance between worker and establishment quality and thus less assortative matches. Starting from the fourth job, job mobility is associated with a more assortative worker-establishment match. Further analyses show that this pattern is particularly profound for low-quality workers, while high-quality workers improve in terms of assortative matching right away. We show that the different matching patterns occur since workers, independently of their own quality, move towards higher-quality establishments at the beginning of the career which then leads to assortative matches for high-quality, but not for low-quality workers. Our results are in line with a job ladder model under the assumption of incomplete and asymmetric information. Lastly, we show that the increase in assortative matching can explain 20-30 percent of the increase in wage inequality over the life cycle pointing to the importance of sorting for (cohort) wage inequality.

In this paper, we have focused on men for technical reasons. Since the data does not comprise working hours, meaningful wage regressions must be restricted to full time workers - which is much more common for men. Repeating our analyses for full-time working women yields qualitatively similar results, especially for high-quality women. However, a remaining question is whether longer breaks in the employment history, like child birth and home work, reset this trajectory and throw women back to less assortative matches. For high-quality workers, this is likely a further source of inequality.

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Appendix

A1 Wage Imputation

Since the data come from social security records, daily wages are censored by the social security contribution limit. We follow Dustmann/Ludsteck/Schönberg (2009) and Card/Heining/Kline (2013) and impute values for censored wages. We fit a series of Tobit models separately by year, skill level and region (East/West) by regressing log wages on non-censored wages and several control variables[6]. We then extend the imputation process by including leave-one-out means as in Dauth/Eppelsheimer (2020). More precisely, we first sum total wages per worker except the current episode's earnings and divide by the total number of employment episodes minus one episode. We then sum wages per establishment and year, subtract worker i's (imputed) wage and divide by all other employees. We repeat the Tobit regressions and include both leave-one-out means as well as dummies on whether there is only one observation per worker and whether the establishment has only one employee. We use the results of this second step as the imputed wages in case where the original wage information was subject to censoring. We cease the imputation by excluding values that are implausible high[7].

[6] The control variables include a dummy on whether the worker is a woman, age, an age polynomial, an interaction of age and a dummy indicating whether the person is more than 40 years old, a similar interaction with age squared, job tenure, tenure squared, a dummy indicating if the establishment has less than eleven employees and the workplace municipality.

[7] We replace imputed values with the value of the 99th percentile (350 Euro) if they lie above the threshold of ten times the value of the 99th percentile.

A2 Summary Statistics

Table A1: Assortative Matching over the Career: Distance Measure

	Number of Workers	Share
1 Job	4,792,123	19.19
2 Jobs	5,509,430	22.06
3 Jobs	4,508,634	18.05
4 Jobs	3,339,296	13.37
5 Jobs	2,349,003	9.41
6 Jobs	1,596,402	6.39
7 Jobs	1,053,975	4.22
8 Jobs	685,474	2.74
9 Jobs	436,021	1.75
10 Jobs	288,912	1.16
11+ Jobs	416,410	1.67

Notes: This table shows how many different jobs we can observe for workers. All jobs between 1975 and 2019 are counted.
Source: IEB, own calculations. ©IAB

Table A2 provides an overview of workers and establishments by job number. We include only observations for which we can identify a person and plant fixed effect as described in chapter 3 since both effects are needed to calculate our measures of assortative matching[8]. Additionally, the sample only consists of the first observation per worker and job. It is important to note that most workers appear in more than one group simply because they have more than one employer over their employment course. The number of jobs differs between workers which can also be seen in the decreasing number of workers in higher job numbers. Simultaneously, the number of establishments decreases as well. Mean daily wages in the fist year of each job start at 98 Euro at the beginning of the career and increase rapidly with the highest mean wage in job number five (116 Euro) but then decreases on average for workers who continue to be mobile. Another interesting feature is the development of establishment size over job numbers. We define establishment size by the number of employees in our sample at the respective plant. Naturally, the true number of employees is higher due to our sample restrictions but as we cover male full-time workers, the true establishment size must be highly correlated with our measure. While in the first job the average number of sample co-workers is 792, the number is substantially lower in the fifth (312) or ninth (176) job. The varying plant size across job groups suggests that plants employing workers with a high number of previous jobs must be different from plants that mainly employ workers at the beginning of their career. Turning to the composition of workers within each group, differences become apparent. Not surprisingly, the average entry age at each job increases with further jobs. While the average worker in our sample is 32 years old at the beginning of their first job, they are on average 47 years old

[8] This can also explain why there are fewer workers in the first job than in the second.

in the ninth job[9]. The shares of high, medium and low skilled workers[10] in each job group could give a first insight on whether it is a specific group that frequently changes jobs. Overall, the medium-skilled workers are the largest group with 74 percent of the sample, followed by 16 percent of high-skilled workers and 10 percent low-skilled. While the shares of medium-skilled workers increases in later jobs, the share of low-skilled decreases. The share of high-skilled workers increases first but decreases after four jobs.

Table A2: Summary Statistics by Job Number

						Skill		
	Workers	Firms	Age	Wage	Size	Low	Medium	High
Job 1	13,739,109	1,741,672	32.369	97.96	792	14.43	65.89	19.69
Job 2	14,161,305	1,979,452	35.824	106.7	525	17.33	71.11	11.55
Job 3	11,269,408	1,826,525	38.507	112.28	430	17.67	74.60	7.73
Job 4	8,191,750	1,577,640	40.625	115.24	362	17.26	77.60	5.57
Job 5	5,678,019	1,308,366	42.39	116.31	312	16.67	79.15	4.18
Job 6	3,816,702	1,053,236	43.875	115.87	269	15.97	80.86	3.17
Job 7	2,505,518	826,508	45.122	114.24	232	15.13	82.45	2.42
Job 8	1,616,728	633,015	46.198	111.75	202	14.11	84.01	1.88
Job 9	1,025,562	471,201	47.121	108.83	176	13.14	85.41	1.45
Job 10	705,322	365,629	47.809	105.17	157	11.51	87.37	1.11
Overall	24,975,680	3,208,466	38.219	108.78	480	16.30	73.91	9.79

Note: Summary statistics only includes observations for which a worker and establishment fixed effect could be estimated. Further, summary statistics are based on the first observation of a worker in each job.
Source: IEB, own calculations. ©IAB

[9] For any workers who do not appear in the IEB prior to 1995, we start counting the first appearance within our sample period as their first job. This possibly includes East German workers or foreign workers which explain the relatively high entry age. We conduct several robustness checks dealing with this and find very similar results.

[10] The IEB includes an imputed education variable, based on Fitzenberger/Osikominu/Völter (2005). This variable has six different values according to the highest education qualification. We follow Dauth/Eppelsheimer (2020) and recode them into three skill levels. Low-skilled workers have no vocational training, a medium skill level corresponds to a vocational training and high-skilled workers obtained a degree at a university or a university of applied science.

A3 Estimation Issues

In order to ensure that our data meet the assumptions of the AKM model, we conduct a couple of analyses as in Card/Heining/Kline (2013). First, we examine the separability assumption. For this purpose we select all job (establishment) changes between 1995 and 2019 where the person worked for at least two consecutive years in both the old and new job. Additionally, the change from one firm to another must be without interruption of employment[11]. We then assign each worker-firm observation to a quartile of the establishment effect distribution and group each job change in one of 16 cells based on the quartile before and after the job change. Finally, we calculate the mean log adjusted wage in each cell. Following Card/Rothstein/Yi (2023) we control for quadratic and cubic age terms as well as year effects. Figure A1 shows the event study of job movers in our sample that leave quartile 1 and 4 employers, meaning the establishments with the lowest (quartile 1) and highest (quartile 4) wage premia. Time period 0 corresponds to the first year in the new firm, -1 to the year prior the change. The vertical axis depicts log daily wages before and after the job change.

The first interesting result is that the wage level prior and after a job change differs for groups coming from the same origin quartile. For example, mean-adjusted wages before the change are higher for workers going from quartile 4 to quartile 3 than for those going to quartile 2. For movers leaving quartile 1, firms with a low estimated establishment effect, the wage differences prior the move by destination quartile are not as distinct. The prediction of pre-move wage level by destination plant quality quartile can be seen as first evidence of sorting based on worker heterogeneity. Further, mobility to a similar firm in terms of quality (1 to 1 or 4 to 4) is not associated with a noticeable wage gain while changes to firms with higher establishment effects are associated with an increase in mean adjusted wages. At the same time, moves to establishments with lower quality are accompanied by wage losses. Like Card/Heining/Kline (2013), we find that wage gains for upward movers and wage losses for downward movers are approximately symmetric. Workers leaving a quartile 4 plant for a quartile 1 plant experience a wage loss comparable to the wage gain for movers in the opposite direction (1 to 4). This can be seen as evidence that the additive structure of the AKM wage decomposition into a worker and firm fixed effect is a good approximation. By definition of the AKM model, the change in mean wages after a move from firm J to K can be described by $\psi_J - \psi_K$, the difference in firm effects of the departure and destination employers. Therefore, a move in opposite direction is linked to a wage change by $\psi_K - \psi_J$ as long as the error term in the model is random. It can also be noted that the wage profiles prior to the job change are relatively flat, so no anticipatory wage dips or rises can be seen. Similarly, the wage profiles are relatively flat in the two years after the move. Following

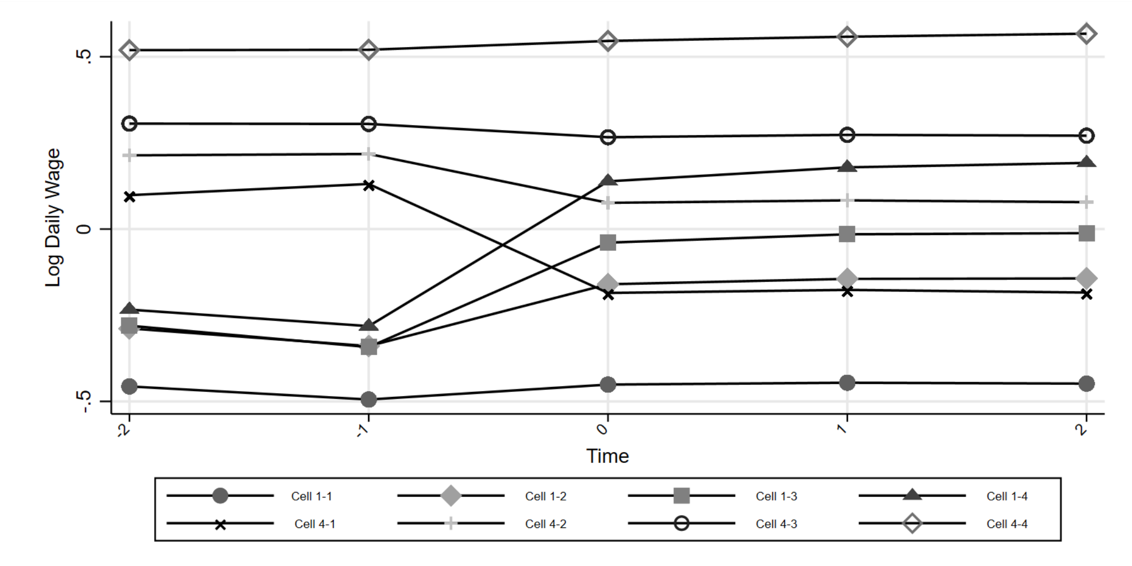
[11] Since we work with a yearly panel this simply means that while a worker works in the old job in year t, they have to work in the new job in $t + 1$.

Card/Heining/Kline (2013), we interpret these flat wage profiles as further evidence that the AKM model provides a good approximation of the wage structure of job movers.

Figure A2 shows the event study of job movers with a different distribution underlying the 16 cells. Here we do not calculate quartiles based on establishment effects but use coworkers' mean wage instead. After determining the coworkers' mean wage for each person-year observation in our job mobility sample we assign each to a quartile of this distribution. Based on origin and destination quartile, each job move is assigned to a cell. Again, we adjust wages by year effects and control for polynomials in age. Most importantly, wage gains and losses of movers in opposite directions are still roughly symmetric indicating that the AKM establishment fixed effects correctly predict wage changes of movers. Further, it becomes even more clear that there must be sorting between plants and workers in our data. The destination cells that are based on coworkers' wages clearly predict wages prior to the move. There are substantial differences in wage levels before period 0 for workers in the same quartile. Those moving to establishments with very higher coworker mean wages earned much more compared to those whose new job is at a quartile 3 or quartile 2 establishment. Interestingly, wage patterns prior and post job changes are not as flat as in Figure A1.

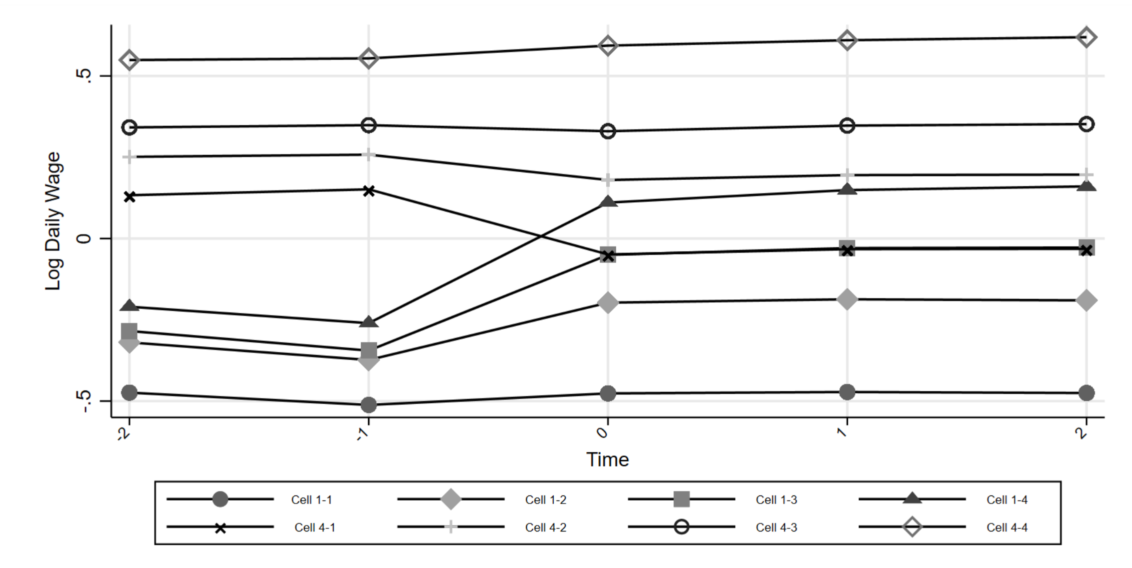
In order to check whether the exogenous mobility assumption is met, initially the event study in Figure A1 and Figure A2 can be of use. As previously described, wage losses and gains of movers in opposite directions are quite symmetric indicating that there is, on average, no match-related wage gain after a job change. If it were the case, then upward-movers would gain more than $\psi_J - \psi_K$. Additionally, the absence of increasing wage patterns for movers within the same quartile (1 to 1 or 4 to 4) contradicts a general mobility premium. Transitory wage shocks that follow an establishment change of affected workers could be another possible violation of the exogenous mobility assumption (Card/Heining/Kline, 2013; Card/Rothstein/Yi, 2023). However, they would lead to decreasing or increasing wage patterns before the move, and pre-move wage patterns are relatively flat. Card/Heining/Kline (2013) introduce a job match model to further assess the importance of any match effects for job movers. The authors expand the AKM model (Equation 1) by job dummies that each consist of a worker-firm combination, but find that these match effects are small and explanatory power of this model only offers a slight improvement compared to the AKM model. Since Card/Heining/Kline (2013) also use IEB data, we interpret their findings as further evidence that the additive AKM structure with the exogenous mobility assumption offers a good approximation of wages in Germany.

Figure A1: Mean Adjusted Wages of Job Movers by Quartiles of Establishment Effects



Notes: All observations are ranked by the estimated establishment effect. Each job mover is assigned to a cell based on the quartile of origin and destination establishment. The figure shows the wage development of a cell's mean wages. Time 0 corresponds to the first year in the new establishment. Only job-to-job moves with at least a duration of two years in origin and destination establishment are considered. Wages are adjusted.
Source: IEB, own calculations. ©IAB

Figure A2: Mean Adjusted Wages of Job Movers by Quartiles of Coworker Mean Wages



Notes: All observations are ranked by coworkers' mean wage. Each job mover is assigned to a cell based on the quartile of origin and destination coworkers' mean wage. The figure shows the wage development of a cell's mean wages. Time 0 corresponds to the first year in the new establishment. Only job-to-job moves with at least a duration of two years in origin and destination establishment are considered. Wages are adjusted.
Source: IEB, own calculations. ©IAB

A4 AKM Results

Table A3: AKM Results

	Workers	Establishments	Mean $\hat{\alpha}_i$	Mean $\hat{\psi}_{j(it)}$
Job 1	13,739,109	1,741,672	-0.076	-0.054
Job 2	14,161,305	1,979,452	-0.074	-0.055
Job 3	11,269,408	1,826,525	-0.067	-0.055
Job 4	8,191,750	1,577,640	-0.061	-0.057
Job 5	5,678,019	1,308,366	-0.06	-0.063
Job 6	3,816,702	1,053,236	-0.062	-0.07
Job 7	2,505,518	826,508	-0.067	-0.078
Job 8	1,616,728	633,015	-0.074	-0.088
Job 9	1,025,562	471,201	-0.083	-0.098
Job 10	705,322	665,629	-0.092	-0.103
Overall	24,975,680	3,208,466	-0.07	-0.059

Notes: The results stem from estimating Equation 1. $\hat{\alpha}_i$ is the estimated person fixed effect and $\hat{\psi}_{j(it)}$ the estimated establishment fixed effect.
Source: IEB, own calculations. ©IAB

A5 Composition of Job Groups

In order to assess assortative matching over the career, all observations are assigned a job number. For example, if a person is in their fifth job in a specific year, this observation is assigned job number five. In a first step, we calculate the correlation between the estimated worker and establishment fixed effects separately for all workers with the same job number. This raises the concern that individuals and establishments are not comparable across job number groups. Table A2 already showed that there are differences in observable characteristics of workers and plants between those groups. While we can control for these differences in in a regression framework that uses the distance between worker and establishment quality as the dependent variable, this is not possible when working with the correlation. To ensure that the correlation results are not driven by these composition effects, we residualize both AKM effects by regressing the estimated AKM effects on a number of variables. In the case of the person fixed effect ($\hat{\alpha}_i$) we control for year effects, skill level, age, tenure of the current job, occupation on a two-digit level and workplace region (East/West) as described in Equation 1. e_i^1 is the residual. Equation 2 shows the residualization of the estimated establishment effect ($\hat{\psi}_{j(it)}$). Control variables include years, municipality of the workplace, sector and number of employees of firm j in time t. Again, e_j^2 is the residual.

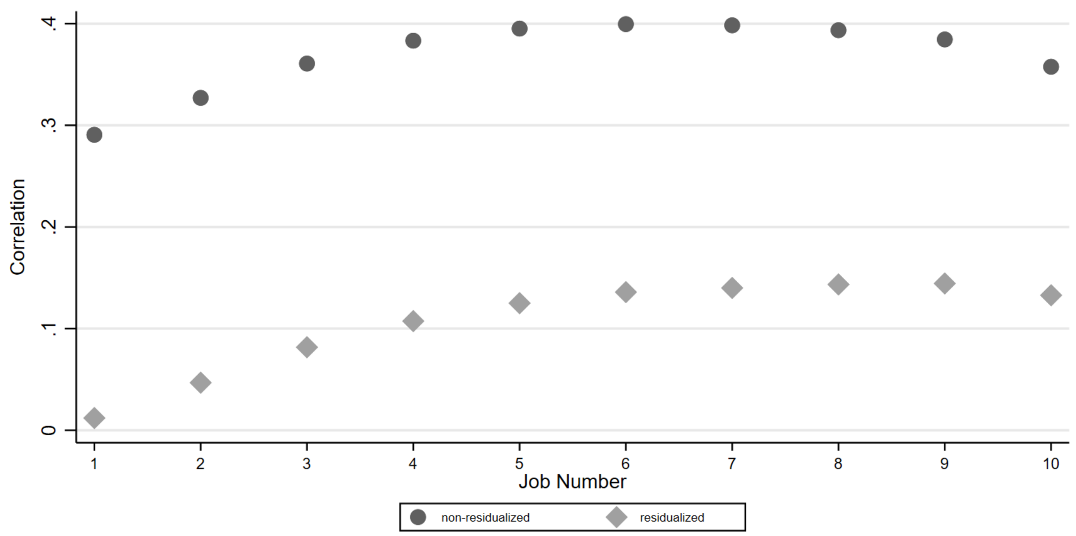
$$\hat{\alpha}_i = \beta^1 X^1 + e_i^1 \tag{1}$$

.

$$\hat{\psi}_{j(it)} = \beta^2 X^2 + e_i^2 \tag{2}$$

Next, we use $\hat{e}_i^1$ and $\hat{e}_i^2$ to calculate the correlation. We call this correlation our adjusted measure of assortative matching. The residualization aims at controlling for any systematic differences of workers and firms between different job numbers. At the same time, it allows us to further decompose the estimated AKM effects. By controlling for observables like year, skill, age, occupation, region, municipality, sector and plant size, in $\hat{e}_i^1$ and $\hat{e}_i^2$, only unobservable time-invariant characteristics remain that are independent of anything we can control for. Hence, the correlation between them as the measure for matching is based on this remaining part of the estimated AKM effects.

Figure A3: Adjusted Worker-Firm Matching over the Career



Notes: The figure shows the correlation between the estimated establishment ($\hat{\psi}_{j(it)}$) and person effects ($\hat{\alpha}_i$) by job number (dark grey). Additionally, the correlation between residualized effects by job number is shown (light grey). AKM effects are obtained from Equation 1.
Source: IEB, own calculations. ©IAB

A6 Robustness

A6.1 Further Robustness Checks

Job Count. The IEB contains data from 1975 for West Germany and includes East German labor market participants since 1992. As described in chapter 2, we use all available employment spells, including those starting before 1995, in order to assign the correct job number. Nonetheless, it is impossible to capture employment before 1975 for West and 1992 for East Germans due to data unavailability. For East Germans whose first job took place before 1992, it can be argued that we capture these workers' first job in a social market economy and thus it is justified to treat these workers as first-time employees. However, West Germans that are actually more experienced than we can observe could be a threat to our baseline results. We conduct three robustness checks to see whether relatively old workers in the first job drive our results. First, we introduce an age restriction for workers in their first job to assess whether it is credible that they are indeed in their first job. Thereby, the age restriction depends on the skill level of the worker at that time. Low-skilled workers must be 20 years or younger, medium-skilled workers 25 years or younger and high-skilled workers 30 years or younger when starting their first job. We analyze the distance between worker and plant quality over the employment course for workers who meet these criteria. Results are shown in Table A6. We find very similar results and conclude that it is unproblematic to rely on the job number that we assigned to the workers.

Second, we investigate to what extent the increase in assortative matching over the career is driven by East Germans for whom we can only use information from 1992 onward. Consequently, for them the risk is higher that they were assigned an incorrect job number. For this robustness check we exclude all workers whose first observed job took place in former East Germany between 1992 and 2000 (6 percent of all workers). We choose this time frame to leave enough time after reunification without generally excluding workers in East German states. Table A7 shows the matching patterns over the employment course. Again, we find similar results compared to our baseline results and conclude that they are not driven by this specific group of workers.

Third, we exclude another group of workers for whom we cannot be sure to observe the first job, namely foreign workers. Since we do not know whether they hold work experience from other countries, they could threat the baseline result. The identification of foreign workers in Germany is based on the worker's nationality. In this robustness check, we exclude all workers who do not hold German nationality at the time of the first job in our sample period. Table A8 shows that our baseline results are robust to excluding foreign workers.

Difference between Worker and Establishment Quality. To define the measure of the distance between worker and plant quality we rely on bins based on their AKM effect distribution. Binning workers and plants with similar AKM effects respectively helps to not put too much weight on outliers in either the worker and plant quality distribution. We check whether our results are sensitive to defining the distance between worker and establishment quality by the raw difference between the estimated AKM effects. Results are displayed in Table A9. It can be seen that our results are similar with those that were obtained with binning workers and establishments in order to calculate the distance between worker and establishment quality.

A6.2 Robustness Check Tables

Table A4: Grouped AKM Estimation: Distance

	(1)	(2)	(3)	(4)
	Dependent Variable: Adjusted Difference			
Job Change	106.6***			
	(2.595)			
Job 2		-74.01***	-30.53***	-20.45***
		(6.582)	(0.0656)	(0.0559)
Job 3		733.4***	-47.31***	-31.52***
		(8.619)	(0.0772)	(0.0662)
Job 4		1225.8***	-56.00***	-37.90***
		(10.46)	(0.0890)	(0.0762)
Job 5		1400.4***	-60.34***	-41.72***
		(12.53)	(0.102)	(0.0872)
Job 6		1211.2***	-62.09***	-43.73***
		(15.04)	(0.118)	(0.100)
Job 7		759.7***	-62.10***	-44.63***
		(18.16)	(0.139)	(0.117)
Job 8		117.7***	-60.64***	-44.56***
		(22.06)	(0.165)	(0.138)
Job 9		-666.2***	-57.71***	-43.45***
		(26.99)	(0.199)	(0.166)
Job 10		-1264.2***	-53.25***	-41.22***
		(32.25)	(0.244)	(0.203)
Constant	45640.2***	45504.2***	46031.7***	46159.3***
	(9.141)	(7.621)	(0.0546)	(3.353)
Worker FE	no	no	yes	yes
Controls	no	no	no	yes
N	64,980,816	64,980,816	64,980,816	64,980,816
R^2	0.000	0.000	0.017	0.325

Notes: The dependent variable is the adjusted absolute distance between worker and establishment quality. It is based on 100,000 person bins that were derived from the distribution of estimated AKM person fixed effects and 100 establishment clusters. Establishment clusters include firms with a similar wage structure. Controls include skill level, region (East/West), 2-digit occupation and sector and plant size. Standard errors in parentheses, clustered on worker level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Source: IEB, own calculations. ©IAB

Table A5: Complete Employment Biographies

	(1)	(2)	(3)	(4)
	Dependent Variable: Absolute Difference			
Job Change	-345.3***			
	(2.242)			
Job 2		-1041.3***	-1434.1***	-980.5***
		(10.65)	(11.30)	(10.69)
Job 3		-1907.0***	-2664.4***	-1895.0***
		(11.86)	(12.98)	(12.48)
Job 4		-2345.8***	-3575.2***	-2547.5***
		(12.99)	(14.49)	(13.99)
Job 5		-2516.5***	-4236.6***	-3016.2***
		(14.52)	(16.32)	(15.70)
Job 6		-2527.4***	-4774.6***	-3404.8***
		(16.67)	(18.70)	(17.84)
Job 7		-2494.5***	-5329.6***	-3815.9***
		(19.66)	(21.87)	(20.62)
Job 8		-2434.2***	-5939.9***	-4267.0***
		(23.71)	(26.12)	(24.35)
Job 9		-2367.0***	-6659.1***	-4787.3***
		(29.27)	(31.94)	(29.48)
Job 10		-1976.6***	-7498.1***	-5368.2***
		(35.36)	(39.44)	(36.21)
Constant	28082.0***	28471.7***	29594.1***	24274.3***
	(9.101)	(9.424)	(9.658)	(758.4)
Worker FE	no	no	yes	yes
Controls	no	no	no	yes
N	29,955,873	29,955,873	29,955,873	29,955,873
R^2	0.001	0.002	0.008	0.178

Notes: Only workers are included for whom we can observe at least the first 18 years of their employment trajectory. The dependent variable is the distance between worker and establishment quality. It is based on 100,000 person and establishment quality bins that were derived from the distributions of worker and establishment AKM fixed effects. Controls include skill level, region (East/West), 2-digit occupation and sector and plant size. Standard errors in parentheses, clustered on worker level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Source: IEB, own calculations. ©IAB

Table A6: Age Restriction in First Job

	(1)	(2)	(3)	(4)
	Dependent Variable: Absolute Difference			
Job Change	-374.0***			
	(2.733)			
Job 2		-928.8***	196.4***	-21.20*
		(11.11)	(11.18)	(10.44)
Job 3		-1235.6***	730.6***	28.28*
		(13.21)	(13.47)	(12.62)
Job 4		-1617.4***	687.3***	-200.8***
		(15.22)	(15.77)	(14.72)
Job 5		-1952.5***	306.4***	-575.2***
		(17.62)	(18.50)	(17.15)
Job 6		-2228.2***	-297.2***	-1090.5***
		(20.62)	(21.81)	(20.06)
Job 7		-2461.1***	-1049.9***	-1681.8***
		(24.39)	(25.89)	(23.67)
Job 8		-2750.6***	-2005.1***	-2386.0***
		(29.20)	(31.05)	(28.19)
Job 9		-2967.4***	-3068.6***	-3185.9***
		(35.32)	(37.59)	(34.03)
Job 10		-2877.5***	-4215.9***	-4020.6***
		(42.11)	(45.55)	(41.14)
Constant	30096.7***	30061.1***	28809.6***	24806.8***
	(10.31)	(9.686)	(8.913)	(669.3)
Worker FE	no	no	yes	yes
Controls	no	no	no	yes
N	21,545,373	21,545,373	21,545,373	21,545,373
R^2	0.001	0.002	0.002	0.203

Notes: Only workers are included who are 30 years or younger in their first job and hold a university degree, 25 years or younger and hold a vocational degrre or are 20 years r younger and hold none. The dependent variable is the distance between worker and establishment quality. It is based on 100,000 person and establishment quality bins that were derived from the distributions of worker and establishment AKM fixed effects. Controls include skill level, region (East/West), 2-digit occupation and sector and plant size. Standard errors in parentheses, clustered on worker level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Source: IEB, own calculations. ©IAB

Table A7: Excluding First Jobs in East Germany 1992-2000

	(1)	(2)	(3)	(4)
	Dependent Variable: Absolute Difference			
Job Change	-517.0***			
	(1.672)			
Job 2		-650.8***	850.0***	449.0***
		(7.434)	(7.994)	(7.416)
Job 3		-1507.2***	868.1***	286.6***
		(8.542)	(9.549)	(8.965)
Job 4		-2226.6***	309.7***	-162.0***
		(9.579)	(10.97)	(10.31)
Job 5		-2744.0***	-437.8***	-684.0***
		(10.88)	(12.58)	(11.80)
Job 6		-3081.3***	-1257.5***	-1237.9***
		(12.58)	(14.52)	(13.57)
Job 7		-3292.2***	-2122.9***	-1820.0***
		(14.82)	(16.96)	(15.76)
Job 8		-3425.9***	-3037.3***	-2434.1***
		(17.74)	(20.07)	(18.56)
Job 9		-3498.4***	-4032.5***	-3114.1***
		(21.60)	(24.14)	(22.20)
Job 10		-3183.0***	-5092.1***	-3835.8***
		(25.67)	(29.23)	(26.81)
Constant	29812.0***	29567.9***	28110.7***	21640.2***
	(6.423)	(6.352)	(6.800)	(420.0)
Worker FE	no	no	yes	yes
Controls	no	no	no	yes
N	57,868,381	57,868,381	57,868,381	57,868,381
R^2	0.003	0.003	0.004	0.196

Notes: We exclude all workers who had their first job in former East Germany between 1992 and 2000. The dependent variable is the distance between worker and establishment quality. It is based on 100,000 person and establishment quality bins that were derived from the distributions of worker and establishment AKM fixed effects. Controls include skill level, region (East/West), 2-digit occupation and sector and plant size. Standard errors in parentheses, clustered on worker level. $^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$.
Source: IEB, own calculations. ©IAB

Table A8: Excluding Non-German Nationality Workers

	(1)	(2)	(3)	(4)
	Dependent Variable: Absolute Difference			
Job Change	-457.2***			
	(1.679)			
Job 2		-959.3***	122.1***	-38.80***
		(7.326)	(7.793)	(7.370)
Job 3		-1736.5***	-10.16	-288.6***
		(8.440)	(9.319)	(8.890)
Job 4		-2324.2***	-529.6***	-714.3***
		(9.481)	(10.72)	(10.22)
Job 5		-2718.4***	-1195.7***	-1185.2***
		(10.80)	(12.32)	(11.69)
Job 6		-2936.0***	-1921.2***	-1692.0***
		(12.54)	(14.29)	(13.47)
Job 7		-3042.2***	-2707.5***	-2242.8***
		(14.84)	(16.78)	(15.71)
Job 8		-3104.3***	-3577.1***	-2845.7***
		(17.85)	(19.99)	(18.59)
Job 9		-3088.5***	-4512.4***	-3505.1***
		(21.85)	(24.20)	(22.36)
Job 10		-2730.5***	-5545.7***	-4228.5***
		(26.17)	(29.51)	(27.15)
Constant	28569.9***	28606.4***	27666.6***	22099.7***
	(6.415)	(6.283)	(6.599)	(449.9)
Worker FE	no	no	yes	yes
Controls	no	no	no	yes
N	55,477,612	55,477,612	55,477,612	55,477,612
R^2	0.002	0.003	0.003	0.173

Notes: We exclude all non-German workers. The dependent variable is the distance between worker and establishment quality. It is based on 100,000 person and establishment quality bins that were derived from the distributions of worker and establishment AKM fixed effects. Controls include skill level, region (East/West), 2-digit occupation and sector and plant size. Standard errors in parentheses, clustered on worker level. $^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$.

Source: IEB, own calculations. ©IAB

Table A9: Definition of Distance Measure

	(1)	(2)	(3)	(4)
	Dependent Variable: $\hat{\alpha}_i$-$\hat{\psi}_{j(it)}$			
Job Change	-0.00361***			
	(0.0000167)			
Job 2		-0.00890***	-0.00386***	-0.00299***
		(0.0000742)	(0.0000683)	(0.0000685)
Job 3		-0.0145***	-0.00633***	-0.00525***
		(0.0000848)	(0.0000803)	(0.0000818)
Job 4		-0.0181***	-0.00914***	-0.00722***
		(0.0000941)	(0.0000911)	(0.0000933)
Job 5		-0.0201***	-0.0118***	-0.00882***
		(0.000106)	(0.000104)	(0.000106)
Job 6		-0.0218***	-0.0146***	-0.0105***
		(0.000123)	(0.000120)	(0.000122)
Job 7		-0.0235***	-0.0174***	-0.0122***
		(0.000145)	(0.000140)	(0.000142)
Job 8		-0.0257***	-0.0206***	-0.0141***
		(0.000173)	(0.000166)	(0.000167)
Job 9		-0.0280***	-0.0239***	-0.0164***
		(0.000211)	(0.000201)	(0.000200)
Job 10		-0.0282***	-0.0274***	-0.0185***
		(0.000252)	(0.000244)	(0.000242)
Constant	0.253***	0.253***	0.248***	0.265***
	(0.0000636)	(0.0000640)	(0.0000564)	(0.00446)
Worker FE	no	no	yes	yes
Controls	no	no	no	yes
N	55,477,612	55,477,612	55,477,612	55,477,612
R^2	0.001	0.002	0.001	0.046

Notes: The dependent variable is the difference between estimated AKM person and establishment fixed effect ($\hat{\alpha}_i - \hat{\psi}_{j(it)}$). Controls include skill level, region (East/West), 2-digit occupation and sector and plant size. Standard errors in parentheses, clustered on worker level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Source: IEB, own calculations. ©IAB

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