The Role of Labor Market Entry and Exports in Sorting: Evidence from West Germany*

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Abstract

The sorting of high-wage workers to high-wage firms accounts for a substantial share of rising wage inequality. Yet, little is known about which worker flows most contribute to sorting or what economic mechanisms have lead to its rise. I make three contributions toward answering these questions. First, to understand how sorting intensifies, I develop a novel decomposition method to measure the relative importance of different worker flow channels. I find that labor market entry of young workers is the dominant sorting channel–accounting for about half of the total rise in sorting–while job-to-job transitions play a more limited role. Second, to understand why sorting is rising, I use exogenous variation in West German trade exposure to estimate the effect of trade liberalization on changes in sorting within local labor markets. Export exposure produces a large, positive effect on sorting and can account for 14% of the total rise in sorting between 1985 and 2009. Third, I apply the worker flow decomposition method to exogenous, export-induced changes in employment. Holding worker composition constant, I confirm that labor market entrants account for about half of rising sorting.

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1 Introduction

The rise in earnings inequality has been widely documented in many developed economies including Germany, the US, and the UK (e.g. Dustmann et al. 2009; Autor et al. 2008; Katz et al. 1993). Traditionally, economists have sought explanations for rising inequality in changing returns to worker characteristics, such as education, occupation, and skill (e.g. Katz and Autor 1999; Acemoglu and Autor 2011). However, recent studies find that earnings are also heavily determined by firm characteristics. This literature documents large variation in firm-specific wage premiums and, over time, an increasing employment of high earning individuals at high-wage firms.[1] In fact, this sorting amongst workers and firms accounts for about 30% of the rise in inequality in both Germany and the US (Card et al., 2013; Song et al., 2015).[2] Yet, despite accounting for a sizable share of rising inequality, very little is known about how or why sorting is rising. To make progress towards this end, I perform three exercises. First, to understand how sorting is rising, I develop a novel decomposition method to quantify the importance of different worker flow channels. Second, to understand why sorting is rising, I estimate the causal effect of liberalization of international trade. Third, I combine the previous exercises by applying the worker flow decomposition to only the changes in employment induced by exogenous trade variation. Holding worker composition constant, this decomposition documents the channels by which labor demand leads to sorting.

I measure labor market sorting based on worker and firm wage components estimated in a fixed effects regression following the methodology of Abowd et al. (1999). The worker component represents the portion of earnings capacity which is portable across all jobs.[3] The firm component represents a firm-specific earnings premium paid to all employees regardless of worker ability.[4] Sorting is then defined as the correlation between worker and firm wage components across jobs. A positive sorting measure means that, on average, high-wage workers are employed at higher-wage firms than low-wage workers. Within this framework, even if the variance of both worker and firm wage components is constant over time, increased sorting can cause higher inequality. For example, given only two workers and two firms, wage variation will be greater if the lower-wage worker is employed by the lower-wage firm, rather than if the lower-wage worker is employed by the higher-wage firm.

[1] For an account of the magnitude of variation due to firm wage premiums see, among others, Abowd et al. (1999); Goux and Maurin (1999); Abowd et al. (2002); Gruetter and Lalive (2009); Holzer et al. (2011); Song et al. (2015).

[2] Bagger et al. (2013) also find increased sorting in Denmark. Håkanson et al. (2015) find that firms are increasingly segregated in terms of worker skills in Sweden–a related concept to sorting.

[3] This component captures any fixed worker characteristics that affect earnings such as education or skill.

[4] One prominent explanation for the existence of firm wage components is that more successful firms share some portion of their rents with their employees. See Card et al. (2018) for an overview of the connection between rent-sharing and firm wage premiums.

Although researchers have identified an increase in sorting, how this process has taken place remains an open question. In particular, we lack an understanding of which worker flows have led to the rise. Sorting is often thought to arise through job-to-job transitions (e.g. Hagedorn et al. 2017; Lopes de Melo 2016) since they account for a large fraction of employment separations (e.g. Fallick and Fleischman 2004) and help to match the magnitude of frictional wage dispersion in search models (Hornstein et al., 2011). However, we lack empirical evidence to verify this conjecture against alternative channels.

To bridge this gap, I develop a novel decomposition method to quantify the relative importance of different worker flow channels to the rise in sorting over time. I classify workers into the following worker flow groups according to their employment history: job-to-job transitions, labor market entry of young workers, and employment-to-nonemployment transitions.[5] By constructing counterfactual joint distributions by worker and firm wage components in which a given channel is held constant, I am able to compare the relative contributions of very different types of worker flows. As a result, this framework offers a comprehensive view of the factors that shape aggregate sorting patterns.

The results of this decomposition show that labor market entry is the most important worker flow leading to rising sorting. In fact, I estimate that labor market entry accounts for 57.0% of the rise. On the other hand, job-to-job transitions play a more limited role, accounting for only 17.8% (with an upper bound of 26.7%). The remaining fraction is due to job stayers (12.8%) and unemployment transitions (2.6%). This decomposition, which I label the *aggregate decomposition*, offers some of the first evidence as to how the sorting process occurs. Despite the focus on job-to-job transitions in the literature, increases in the initial sorting of young workers in their first jobs is a more important channel for rising sorting.

Next I move on to the question of why sorting is rising. Of the multiple potential causes, I focus on the role of trade.[6] Most theories of sorting are based on the idea that high-skill workers are especially productive at high-productivity firms. By increasing the scale of the market, export exposure may strengthen these complementarities between workers and firms and lead to greater sorting (Bombardini et al., 2015). In addition to the theoretical interest in the effect of trade on sorting, trade liberalization is also an empirically significant channel. In fact, the value of exports as a percentage of German GDP rose from 22% in 1988 to 39% in 2006.[7]

To identify this channel I exploit the surge in German trade after the fall of the Soviet Union

[5] Employment-to-nonemployment transitions include transitions to unemployment and other unidentified states such as non-participation, self-employment, part-time employment, and employment in East Germany or foreign countries.

[6] Some other potential causes are technological change, changes in the skill distribution, and changes in the degree of search frictions.

[7] As this statistic fluctuates annually, these numbers represent seven year averages in which the indicated year is the median of the interval (source: OECD).

and the rise of China in the 1990s and 2000s. Following the methodology of Autor et al. (2013) and Dauth et al. (2014), I construct measures of import and export exposure based on the value of trade between Germany and Eastern Europe and China (the "East") at the local labor market level. The rise of trade with the East had differential impacts across German *industries* and, therefore, differential impacts across German *regions*. This variation can be credibly argued to be exogenous to domestic supply and demand variation across industries since these events were largely motivated by internal politics within the East. Furthermore, both regions ascended to World Trade Organization membership around 2001, representing a second exogenous shock to terms of trade. This research design aims to identify changes to labor demand induced by changes in foreign product supply and demand, while excluding effects due to changes in domestic factors.

I estimate a significant, positive causal effect of export exposure on local labor market sorting. In contrast, import exposure shocks have an insignificant, negative effect on sorting. Using the average change in trade exposure over the period, I find that trade shocks from the East can account for a substantial share (14%) of the total rise in West German sorting. Furthermore, I show that export exposure shocks increase manufacturing employment and wages and, therefore, substantiate the interpretation of export shocks as labor demand shocks. These results suggest that trade liberalization is an important factor driving increased sorting.

In the final part of the paper, I connect the previous exercises to examine whether the increase in sorting at labor market entry is caused by changes in labor demand or labor supply. On the supply side, the aggregate decomposition may be affected by trends toward higher education at the top end and waves of low-skill immigration at the bottom end. In order to disentangle the effects of changes in the composition of supply from changes in demand, I apply the worker flow decomposition to changes in employment induced by exogenous variation in export exposure. Recall that the trade instrument is specifically designed to isolate the effect of demand. I then compare the aggregate decomposition with the export decomposition to understand whether the effects of demand are similar to the aggregate effects.

In performing this decomposition, which I label the *export decomposition*, I find very similar results to the aggregate decomposition. Labor market entry is the most important channel for rising sorting–accounting for 47.0%. Job-to-job transitions again account of limited share at 16.6% with an upper bound of 26.4%. Furthermore, I find that these entry effects are in large part driven by the entry of low-wage workers to low-wage service firms. Given that these sorting effects are driven by the demand side, the results suggest that, over time, even if the distribution of workers entering the labor market is the same, sorting will increase due to the demand effects of trade liberalization and other factors that work through similar channels.

1.1 Contribution to the Literature

My main contribution is to provide empirical evidence about the relative roles of different workers flows in labor market sorting. To date, the literature focuses on changes in the allocation of workers to firms after entry into the labor market, arising through job-to-job or employment-to-nonemployment (or unemployment) transitions. Most of the emphasis is on job-to-job transitions since they occur at about twice the rate of employment to unemployment transitions (Fallick and Fleischman, 2004; Nagypál, 2008) and since they fuel the faster growth of high productivity firms (Haltiwanger et al., 2017a). As a result, models of sorting often incorporate on-the-job search in order to match data on worker flows.[8] These models are consistent with the idea that technological shocks require a reallocation of the workforce, which is accommodated through job-to-job transitions. To my knowledge, Haltiwanger et al. (2017b) provide the only direct empirical evidence to assess the role of job-to-job transitions in labor market sorting. Perhaps surprisingly, they find that job-to-job transitions act to mitigate assortative matching as low-wage, low-educated workers are more likely to move up the job ladder to high-wage, high-productivity firms. However, they do not produce a comprehensive framework to compare the effect of job-to-job transitions with other worker flows. In developing such a comprehensive framework, I find that one of the most important channels driving sorting, labor market entry, has heretofore been neglected by the literature.

The finding that the growth in sorting occurs at labor market entry has implications for the study of inequality and persistence in the labor market. Guvenen et al. (2017) use data from the US Social Security Administration to study the sources of lifetime inequality. They find that increases in lifetime inequality are primarily the result of increases in the variance of earnings at labor market entry rather than increases in the variance of life-cycle growth paths. Taking a structural approach, Huggett et al. (2011) reach a very similar conclusion using PSID data. My findings with German data are consistent with these results and suggest that increases in the variance of starting wages may result from changes in initial sorting. Additionally, growth in sorting at labor market entry suggests that the factors that generate individuals' initial productivity, such as education, childhood environment, or occupational choice, have a greater effect in determining the type of firm individuals are employed at over time. Also, the fact that reallocation is stronger at entry than over the life-cycle points to persistent sorting effects consistent with other studies that find persistent wage effects with respect to entry conditions (Kahn, 2010; Oreopoulos et al., 2012).

Next, I add to the literature studying the role of exports in sorting. Most theories of sorting are based on an assumption of complementarity in production between heterogeneous worker and firm types. In other words, high-skill workers are particularly productive at high-productivity firms. A classic result in a frictionless environment is that the optimal allocation is characterized

[8] See Eeckhout and Kircher (2011); Hagedorn et al. (2017); Lopes de Melo (2016); Bagger and Lentz (2017); Lise and Robin (2017).

by *assortative matching*, i.e. employment matches are symmetric such that the highest type worker matches with the highest type firm and the lowest type worker with the lowest type firm (Becker, 1973). In an environment with search frictions, each firm tolerates some deviation from the optimal allocation and, therefore, is willing to hire workers within a *matching set* (Shimer and Smith, 2000). Trade has been theorized to increase sorting by shrinking the size of the matching set so that the market allocation approaches the optimal allocation (Bombardini et al., 2015). Growth in export opportunities increases the size of the market, increases demand, and, hence, increases the value of output for any given match. As a result, firms have a higher willingness to pay to find an optimal match, shrinking the matching set and increasing sorting.[9]

A few recent studies have found empirical evidence for the connection between trade and sorting. Whereas as I focus on the effect of export exposure on sorting within German local labor markets, Davidson et al. (2014) find that reductions in export tariffs increase within-industry sorting in Sweden. They also find insignificant negative effects of increases in import tariffs. Their identification strategy relies on the fact that Sweden is a small country and, therefore, has limited ability to influence tariffs set by the European Union. The similarity of the Davidson et al. (2014) results, despite using data from a different country and employing a different identification strategy, suggest that the effect of exports on sorting may have applicability beyond West Germany. Bombardini et al. (2015) study the effect of exports on sorting by assessing some predictions of their model using French data. They find evidence that exporting firms employ a more homogeneous workforce, which they interpret as evidence that exporting firms increase sorting in the labor market. I add a detailed analysis of the effects of trade on worker flows both within and between industries to understand how exporting leads to sorting. Consistent with trade theory, I find evidence that export exposure increases sorting within the manufacturing industry. However, I also find that export exposure has important effects on the service industry with the entry of low-wage workers to low-wage firms. My findings are also relevant to a literature studying the effects of trade exposure on long-term earnings and employment dynamics (Autor et al., 2014; Dauth et al., 2016; Müller et al., 2016), but which does not explicitly consider sorting.

Finally, I add to a small literature which seeks to quantify the sources of rising sorting. In their study of the effects of outsourcing on the labor market in West Germany, Goldschmidt and Schmieder (2017) estimate that outsourcing is responsible for approximately 8% of the rise in West German sorting.[10] Although this may be a lower bound due to a strict definition of outsourcing, the

[9] Davidson et al. (2008) and Helpman et al. (2010) construct trade models with labor market search that reach similar conclusions about the relationship between trade liberalization and sorting. The result that increased match output leads to a reduction in the matching set rests on the assumption of capacity constraints in hiring which lead to opporuntity costs in selection of the appropriate worker. See Eeckhout and Kircher (2011) for a detailed discussion.

[10] Goldschmidt and Schmieder (2017) compute counterfactual moments for the variance of establishment fixed effects and the covariance of establishment and worker fixed effects. Unfortunately, they do not state the value of the variance of worker fixed effects in their sample. Therefore, I take this value from Card et al. (2013) to compute

fact that trade from only Eastern Europe and China can account for 14% of the total rise in sorting suggests that exports are an important source of sorting. In addition, the worker flow channels through which trade affects sorting are similar to the aggregate channels. Therefore, more general increases in demand, including both domestic and international sources, may potentially account for a large share of the total rise in sorting.

2 Data

I use labor market data from the German Social Security system provided by the Institute for Employment Research (IAB) based on the Integrated Employment Biographies (IEB) datafile. Employers are required to submit a notice of employment for all employees and trainees subject to social security, which covers approximately 80% of all employment in West Germany. The major excluded groups are the self-employed and civil servants. Annual employment notifications include information on job duration and earnings for each employment spell. Hours of work are not disclosed, but employees are classified as part-time when working less than 30 hours per week.[11] The administrative data also includes the establishment identification number (EID), industry, and district of the establishment; and the individual identification number, year of birth, gender, education, and occupation of the individual. EIDs are uniquely assigned on the basis of ownership, municipality, and industry.

The main disadvantage of IEB earnings data is that it is censored at the highest level of earnings subject to social security contributions. This results in censoring of 10 to 14% of observations between 1985 and 2009 including about one third of white-collar workers (Card et al., 2013; Schank et al., 2007). Thus, I apply a Tobit wage imputation procedure following Card et al. (2013) and Dustmann et al. (2009) including lifetime and co-worker earnings variables.

Following Card et al. (2013), I restrict the sample to full-time employment in West Germany between the ages of 20 and 60 from 1985 to 2009. I limit earnings to one establishment per year and, therefore, select only the *main job*–defined as an employee's highest earning establishment. Employees in part-time and marginal jobs as well as trainees are excluded. I deflate all earnings to 2010 levels using the German CPI provided by Federal Reserve Economic Data (FRED).

I utilize a variety of datasets prepared by the IAB. For the analysis of earnings and employment I primarily use the Sample of Integrated Labour Market Biographies (SIAB) 1974-2010. The SIAB is a 2% random sample of individual employment histories and, thus, permits longitudinal analysis. To calculate a measure of sorting, I merge worker and establishment fixed effects estimated from

the correlation of establishment and worker fixed effects noting that Goldschmidt and Schmieder (2017) perform the Abowd et al. (1999) estimation procedure with similar data and specification as Card et al. (2013).

[11] Using the German Socio-economic Panel, Dustmann et al. (2009) provide evidence that the variance of hours worked was constant in West Germany after 1990.

the full IEB universe for West Germany in Card et al. (2013). Estimating the AKM methodology in small samples can finite sample bias. Hence I use fixed effects from Card et al. (2013) instead of estimating them with the 2% SIAB.

To construct trade shocks I use the United Nations Commodity Trade Statistics Database (Comtrade) which provides annual statistics of over 170 reporter countries detailed by commodities and partner countries. Using a correspondence between SITC rev 3 product codes and NACE 3-digit industry codes provide by Dauth et al. (2014), I translate trade flows from commodity to industry codes. In order to obtain an accurate count of employment shares within county-industry cells, I aggregate employment from a 50% sample of the IABs Establishment History Panel (BHP) which is an establishment level dataset covering the universe of German establishments subject to social security contributions.

For the purposes of this study, a LLM is defined as a *kreis* which roughly corresponds to a US county. The average population a West German kreis is approximately 200,000.

To illuminate firms' response to trade shocks, I use the Linked-Employer-Employee-Data from the IAB (LIAB) Longitudinal Model 1993-2010. The LIAB is based on a survey of establishments, known as the IAB Establishment Panel. This survey draws a stratified sample of establishments based on industry and establishment size, where large establishments are oversampled. Respondents are followed over time, creating a longitudinal account of annual sales and investment at the establishment level. Participation is voluntary, but the response rate is around 80% (Baumgarten, 2013). The LIAB is produced by merging IEB data with the IAB Establishment Panel by year and establishment.

3 Background on Sorting

3.1 AKM Model

I estimate agent types based on wage components from the Abowd, Kramarz and Margolis (1999) [AKM] regression model which captures fixed unobservable heterogeneity for both workers and firms through following regression equation:

$$y_{it} = \alpha_i + \psi_{j(i,t)} + x'_{it}\beta + r_{it} \tag{1}$$

for log wage y of individual i in year t. Worker heterogeneity is captured by the fixed effect α_i which represents the portion of an individual's earnings capacity that is fully portable across employers. Establishment heterogeneity is modeled with the fixed effect $\psi_{j(i,t)}$, where $j(i,t)$ is a function mapping workers to firms in each year. The establishment fixed effect captures a proportional pay premium common to all workers at establishment j. The fixed effects are identified off of wage variation induced by worker movements between firms. Time-varying worker characteristics x_{it} include year dummies and quadratic and cubic age terms interacted with educational attainment.[12] The controls for age by education effectively control for five separate experience gradients.[13] Although I suppress additional notation, this equation is estimated for four separate seven-year intervals p over the period 1985 to 2009. This flexibility allows worker and firm fixed effects to change over time within the same individual or firm.

Consistent estimation of the parameters of equation (1) relies on the standard OLS identification assumption of conditional orthogonality of the error term r_{it}. In this context, Card et al. (2013) argue that identification primarily rests on an assumption of *exogenous mobility*, i.e. conditional on fixed effects and observable characteristics, movements between establishments are random. A controversial implication of this assumption is that job transitions are independent of worker-firm specific wage components that may arise, say, due to the presence of complementarities between worker and firm types in the production function.[14]

Although the exogenous mobility assumption is potentially restrictive, Card et al. (2013) provide evidence that this simple model fits the data well and is, therefore, a useful approximation of the wage equation. First, they estimate equation (1) with a interaction term η_{ij} in place of the worker and establishment effects. It is possible to identify either firm and worker effects or match effects, but not both at the same time. Although, the match effect model fits better, the reduction in the root mean squared error is relatively small–on the order of 10-15%–suggesting a limited role for match effects. Furthermore, they measure wage changes as workers move between firms with different average wages–a measure that does not rely on the AKM model structure. They show that wage gains from moving up the firm distribution are very similar to the wage losses from down the firm distribution. This symmetry result is consistent with the log separable form of the AKM estimation equation.[15]

In a different approach to the estimation of firm and worker heterogeneity in wage components, Bonhomme et al. (2016) simplify the space of potential firm effects into firm *classes*. They categorize each firm into one of ten classes based on its wage distribution using a clustering algo-

[12]The linear term of age is omitted because it is not separately identified from the year effects.

[13]The Card et al. (2013) education groups are university, some college, apprentice, dropout, and missing.

[14]Given that the wage equation is specified in terms of log wages, the model can be rationalized with a specific form of complemarties in which the production function of worker type x and firm type y is specified such that match output, $f(x, y)$, is equal to xy.

[15]Symmetric wage changes are also found in Portugal (Card et al., 2015) and the US (Song et al., 2015). However, there is also evidence against the exogenous mobility assumption. Abowd et al. (2017) propose a test of the exogenous mobility restriction. Using the Longitudinal Employer Household Dynamics (LEHD) data set, they reject the null hypothesis of exogenous mobility. Woodcock (2015) finds evidence for match effects using a mixed-effect estimator that allows correlation with time-varying observable worker characteristics, but requires the set of random effects to be orthogonal. Thus there is evidence of statistically significant match effects, but they do not appear to account for a large share of total wage variation.

rithm. They then treat firm classes as discrete fixed-effects and worker types as random-effects. This hybrid method reduces the number of worker and firm types and, therefore, enables the explicit estimation of interaction effects between firm and worker types.[16] Although their estimates suggest some departure from log additivity of firm and worker components, they find that log additive models, such as AKM, provide a very good approximation of the wage equation.[17] In other words, the interaction effects representing worker-firm specific components are not quantitatively significant. Therefore, with a variety of methods the AKM equation estimation has been found to approximate the wage equation well.

3.2 Identifying Sorting

I measure sorting as the correlation between AKM worker and establishment fixed effects. A distinction, however, must be made between measures of sorting based on wage components versus productivity components. Assortative matching on wage components has direct implications for inequality as high-wage workers work at high-wage firms. However, wage components may or may not represent productivity types. Other factors may affect firm wages besides productivity such as compensating differentials, bargaining strength, search frictions, or the opportunity costs of hiring workers given job scarcity. Therefore, sorting on wage components may reflect other factors besides worker-firm productivity complementarities.

The literature on sorting is largely focused on identifying the nature of complementarities in the production function in order to draw implications for aggregate efficiency. Earlier studies often interpreted negative or small correlations of AKM wage components as evidence against an interpretation of worker and firm types as complementary.[18] Subsequently, two key critiques were leveled against using AKM wage components to identify sorting of productivity types–one theoretical and the other empirical.

Eeckhout and Kircher (2011) caution against using AKM wage components to infer the sign of production complementarities due to theoretical inconsistencies between wage and production components. Using a simplified search model with positive assortative matching in the tradition of Shimer and Smith (2000) and Atakan (2006), they derive an analytical expression for the firm fixed effect. They show that the ranking of the firm fixed effect does not correspond to the ranking for firm productivity. Due to capacity constraints in the number of available jobs, firms face an

[16] Card et al. (2013) estimate match effects, but not in the same regression as worker and firm effects. Estimating such a regression would require that every worker worked for every firm. By narrowing the type space, Bonhomme et al. (2016) can estimate a full model with separate effects for firm, workers, and their interactions.

[17] The R^2 increases from 74.8% in the model without interactions effects to only 75.8% with in the model with interaction effects (in the static version).

[18] See Abowd et al. (1999) for France; Abowd et al. (2002) for Washington State; Iranzo et al. (2008) for Italy; Gruetter and Lalive (2009) for Austria; Bagger and Lentz (2017) for Denmark; Lopes de Melo (2016) for Brazil; among others.

opportunity cost of hiring a suboptimal worker type. If a worker is employed by a firm with lower productivity than her optimal match, she will earn less due to low match output. On the other hand, if a worker is employed by a firm with higher productivity than her optimal type, she will also earn less. In this case the firm must be compensated for the opportunity cost of not hiring its optimal worker type. As a result, workers experience a non-monotonic relationship between wages and firm productivity and achieve the highest wage at their optimal match.[19]

Although the results that follow can be strictly interpreted in terms of wages components, in settings where both employer-employee wage data and firm outcome variables are present, firm fixed effects are positively correlated with measures of firm productivity. Using German data, Card et al. (2013) find a positive correlation between firm fixed effects and firm survival. With Portuguese data, Card et al. (2015) find a significant and positive relationship between firm fixed effects and log value-added per worker. Using Swedish data, Davidson et al. (2014) find positive correlations of firm fixed effects and a variety of measures of firm productivity including labor productivity, size of capital stock, size of workforce, capital intensity, the ratio of R&D to sales, and the ratio of exports to sales.

The theoretical critique of AKM relies on a large role for opportunity costs in hiring as a result of capacity constraints. However, a model without capacity constraints can rationalize the AKM wage equation with sorting based on worker-firm production complementarities. To drive this point home, I construct a stylized model with these features in Appendix C. I model the process of firm-worker matching through the firm's recruitment decision in an environment with search frictions and bargaining. Firms can increase their chance of finding a worker of a given type by increasing recruitment expenditure. I derive conditions for assortative matching based on the properties of the recruiting cost function. I show that complementarities between worker and firm types in recruitment costs must be stronger than complementarities in the production function to induce positive sorting. Thus high-type firms must face a lower cost of recruiting high-type workers. Such a feature can be rationalized through job referral networks or preferences over amenities that induce high-type workers to exert more search effort in finding high-type firms.[20] Therefore, the interaction of productive complementarities with other sorting mechanisms lead to assortative matching. The model features a wage equation that is log separable in firm and worker components. Furthermore, the wage components map to productivity types. See Appendix C for a full exposition of the model. [21]

[19] In a related paper, Lopes de Melo (2016) reaches a similar conclusion.

[20] See Card et al. (2016) for an outline of a model which can produce sorting based on preferences for amenities by skill groups. See Schmutte (2014) for the role of job referral networks in facilitating the matching of high-ability workers to high-paying firms.

[21] Bagger and Lentz (2017) also present a model of sorting without capacity constraints. Due to the complexity of their approach, the wage equation is not strictly log separable. However, the model can be consistent with and AKM wage equation when workers have substantial bargaining power.

In the end, the importance of these theoretical limitations depends on the magnitude of the opportunity cost of hiring a suboptimal worker type. If workers can be replaced easily or if firms have an unsatiated demand for labor, mismatch will not be costly, and, therefore the AKM approach will provide an accurate approximation of the wage equation. To provide an estimate of the magnitude of opportunity costs, note that non-monotonic wage effects like those derived in Eeckhout and Kircher (2011) would load into worker-firm specific match effects. However, as previously noted, Card et al. (2013) show that match effects account for a modest share of wage variation and Bonhomme et al. (2016) find a limited role for work-firm specific components in a more flexibly specified model.[22]

The literature has also documented an empirical challenge in computing wage component sorting using the AKM components. Estimating the vast number of parameters in the AKM equation can produce a finite sample bias known as *limited mobility bias* (Andrews et al., 2008), which results when there are few job switchers per firm. Intuitively, as the two fixed effects roughly add up to total wages, deviations in the firm fixed effect caused by sampling error are counteracted by deviations in the opposite direction in the worker fixed effect. The result is a negative bias in the correlation of worker and firm effects caused by sampling error. In small samples or in samples with few movers, researchers often get negative estimates of the sorting. When researchers use larger samples, positive correlations are typically found (Card et al., 2013; Song et al., 2015). However, the level of sorting is not likely to be meaningful even in large samples. Therefore, I follow the literature and consider changes in sorting over time. This will work as long as the bias is stable over time. Card et al. (2013) provide evidence that the distribution of movers per firm is stable over time in the West German sample.

Due to a variety of estimates using both structural and more flexible econometric techniques, a consensus is emerging that there is positive sorting in the labor market. This is true in terms of sorting on both productivity and wage components.[23] Although there is strong evidence of positive sorting, less attention has been given to how sorting is evolving over time. Relying on evidence that suggests the AKM approach is an accurate approximation of the wage equation, I measure changes in sorting based on the AKM wage components. In this approach, worker- and firm-types are estimated for each agent. The AKM approach, therefore, facilitates the analysis of the effects of worker flows on changes in labor market sorting.

[22]Song et al. (2015) also reach a similar conclusion with US data.

[23]For structural estimates of positive sorting on productivity components see Hagedorn et al. (2017), Bagger and Lentz (2017), Lopes de Melo (2016), and Lise et al. (2016). A notable exception is Gulyas (2016). For estimates of positive sorting in wage components, see Card et al. (2013) and Song et al. (2015) using AKM on large datasets; Bonhomme et al. (2016) and Borovicková and Shimer (2017) for econometric approaches that don't rely on AKM. Bartolucci et al. (2015) find positive sorting with worker wage components and firm profits.

3.3 Trends in Inequality and Sorting

West German wage inequality rose substantially over the three decade period from 1980 to 2010. Using German social security data, Dustmann et al. (2009) find a 0.6 log point annual increase in the 85/50 earnings ratio from 1975 to 2004. For perspective, the 90/50 ratio rose one log point per year over the same period in the US (Autor et al., 2008). Building on this result, Card et al. (2013) decompose the change in the variance of log wages into worker and firm components. Perhaps surprisingly, they find that firms contribute substantially to rising inequality.

Estimation of equation (1) allows for a straightforward decomposition of the variance of log wages into the following components:

$$\begin{aligned} \text{Var}\left(y_{it}\right) &= \text{Var}\left(\hat{\alpha}_i\right) + \text{Var}\left(\hat{\psi}_{j(i,t)}\right) + \text{Var}(x_{it}'\hat{\beta}) + \text{Var}(\hat{r}_{it}) \\ &+ 2\text{Cov}\left(\hat{\alpha}_i, \hat{\psi}_{j(i,t)}\right) + 2\text{Cov}\left(\hat{\alpha}_i, x_{it}'\hat{\beta}\right) + 2\text{Cov}\left(\hat{\psi}_{j(i,t)}, x_{it}'\hat{\beta}\right). \end{aligned} \tag{2}$$

Card et al. (2013) show that the primary drivers of the change in wage variance are the variance of worker effects (39%), the covariance of establishment and worker effect (34%), and the variance of establishment effects (25%). Therefore, the sorting of establishments and workers, as indicated by the covariance term, emerges as an important contributor to German wage inequality. In fact, in a counterfactural in which a more precise measure of sorting, the *correlation* between establishments and workers, is held constant they estimate that sorting accounts for 31% of the rise in total wage variance. Song et al. (2015) apply the AKM methodology to the US Social Security Administration data and find a strikingly similar result in that earnings variance rises to only 70% of its actual level between 1980 and 2013 with the correlation between firm and worker effects held constant.

3.4 Sorting in Local Labor Markets

I define sorting as the correlation of worker and firm fixed effects within a given local labor market (LLM) or:

$$Corr_l^p\left(\hat{\alpha}_i, \hat{\psi}_{j(i,t)}\right) \tag{3}$$

where l and p denote LLM and estimation interval, respectively. I compute a job-weighted correlation to represent sorting at the worker level.[24] Table 1 compares measures of national and LLM sorting. Columns (1) through (4) present the level of sorting in each interval while column (5)

[24]The statistic, therefore, describes how likely it is for a high-wage worker to work at a high-wage firm, as opposed to a firm-weighted measure that would describe the relationship between firms and their average worker fixed effect. Since the firm distribution is high-skewed such that there are a few very large firms and many very small firms, a firm-weighted measure places greater weight on small firms.

presents the change from the first to last interval. Despite a lower level of sorting, the changes in average LLM sorting are equal to the change in national sorting. The same cannot be said for average within-industry sorting. The rise in this measure is roughly half of the total rise. Women have a lower level and a smaller rise in sorting. However, within-LLM sorting is once again similar to the national change in sorting. Since the rise of LLM sorting mirrors the national rise, I use within-LLM measures to understand changes in national sorting.

Table 1: Correlation of Establishment and Worker Fixed Effects over Time

		Int 1 '85-'91 (1)	Int 2 '90-'96 (2)	Int 3 '96-'02 (3)	Int 4 '03-'09 (4)	Change 1 to 4 (5)
	National	0.051	0.114	0.191	0.282	0.231
Male	Average Within-LLM	0.019	0.081	0.156	0.248	0.229
	Average Within-Ind	0.024	0.077	0.092	0.143	0.120
	National	0.042	0.088	0.097	0.137	0.095
Female	Average Within-LLM	0.022	0.063	0.071	0.111	0.088
	Average Within-Ind	-0.076	-0.030	-0.046	-0.012	0.064

Notes: "National" refers to the aggregate correlation of worker and establishment fixed effects over time the full sample. "Average Within-LLM" refers to a region-size weighted average of within-local labor market correlations of worker and establishment fixed effects. "Average Within-Ind" refers to the average within three-digit industry correlations of worker and establishment fixed effects.

4 Decomposition of Changes in Sorting into Worker Flows

In order to better understand the forces behind rising sorting in Germany, I decompose the total change in sorting into six categories based on worker transitions across seven-year intervals. The main forces of interest are *labor market entry*, *reallocation*, nonemployment, and *amplification*. For each flow, I compute the net effect defined as the difference between employment measures of entrants in the lead interval minus employment measures of exiters in the lag interval.

Labor market entry denotes a cohort effect measured as the difference between the employment status of labor market entrants relative to exiters. Entrants are defined as individuals who are below the minimum age threshold (20 years) in the first interval and then become employed in the second interval. Labor market exit is the reverse situation in which an employed worker in the first interval passes over the maximum age threshold (60 years) in the second interval. Therefore, labor market entry is in part reflects a mechanical relationship with age.

Reallocation refers to job-to-job transitions. This is a natural channel in which we may expect sorting to arise as it represents job switches for workers with high labor force attachment. I identify reallocation both within and between LLMs.

Nonemployment refers to net movements from of unemployment and a residual category called "other". The administrative dataset includes accurate information on unemployment duration as the German SSA is also responsible for the administration of unemployment benefits. As long as a worker has previously been employed, the coverage of the unemployed population is almost universal. Entering flows from unemployment refer to individuals who are unemployed in the first interval, but become employed in the second interval. Exiting flows refer to individuals who transition from an employed to an unemployed state between intervals.

The employment category "other" refers to individual who are not unemployed but do not have a valid Card et al. (2013) fixed effect. This includes a variety of possible states including out of the labor force, employed in East Germany, part-time work, work in marginal jobs, self-employment, some civil servant employment, employed but not in the largest connected set of firms, immigration and emigration, and death. Analogously to the unemployment flows, I define entry as a transition from other to employment between the initial and subsequent intervals and exit as the inverse sequence. Given that the other category includes employment states, classification of this flow as an entry and exit flow versus a reallocation flow remains ambiguous.[25]

Job stayers denote the group of workers than stay employed at the same firm between intervals. This category quantifies the relative contribution of job stayers to changes in measured sorting. The correlation of establishment fixed effects (EFEs) and worker fixed effects (WFEs) can change due to changes in fixed effect values within a stable match. As the fixed effects are independently estimated in four intervals, I allow for this possibility. Amplification arises from changes in fixed effects that are correlated with initial conditions. For instance, suppose worker x is hired by firm y and both are at the top of their respective fixed effect distributions. If all worker-firm matches stay the same and all fixed effects are constant except that either the WFE of x or the EFE of y increases, then measured sorting will increase. Thus, amplification can arise due to either changes in WFEs that are correlated with initial EFE levels, changes in EFEs that are correlated with initial WFE levels, or changes in EFEs that are correlated with changes in WFEs.

4.1 Methods

The goal of the worker flow decomposition is to understand which worker flows are important for rising sorting. Sorting, defined as the average LLM correlation between WFE and EFEs, is a function of the joint distribution of WFE and EFEs. The idea, therefore, is to estimate an approximation of the joint distribution over time, and then perform counterfactual exercises in which worker flow

[25] Subsequent results provide evidence that this flow behaves more like a reallocation than a flow from unemployment.

channels are sequentially shut down. The worker flow components of sorting can be computed by taking the correlation over the counterfactual joint distributions. This method estimates the total effect of a given flow which may comprise both within and between worker-flow-group effects.

I approximate the joint density by computing WFE and EFE quintiles within LLMs in each period. The resulting joint distribution is a five by five grid of 25 cells designating employment shares. Define $\pi_{ij}^{p} \equiv \frac{E_{ij}^{p}}{E^{p}} \equiv \frac{\sum_{l=1}^{L} E_{ijl}^{p}}{\sum_{l=1}^{L} E_{l}^{p}}$ as the weighted average share of LLM employment in each WFE quintile i and EFE j and estimation interval p.[26] A measure of sorting for each period p across this simplified distribution can be computed as:

$$\rho^{p} \equiv \mathit{Corr}\left(\pi_{ij}^{p}\overline{\alpha}_{i}^{p}, \pi_{ij}^{p}\overline{\psi}_{j}^{p}\right) \tag{4}$$

for all i, j in $\{1, 5\}$, where $\overline{\alpha}_{i}^{p}$ denotes the average WFE in quintile i and $\overline{\psi}_{j}^{p}$ denotes the average EFE in quintile j. The change in sorting can be written as:

$$\triangle\rho \;=\; \mathit{Corr}\left(\pi_{ij}^{p+1}\overline{\alpha}_{i}^{p+1}, \pi_{ij}^{p+1}\overline{\psi}_{j}^{p+1}\right) - \mathit{Corr}\left(\pi_{ij}^{p}\overline{\alpha}_{i}^{p}, \pi_{ij}^{p}\overline{\psi}_{j}^{p}\right). \tag{5}$$

Note that the lead period employment share can be re-formulated as:

$$\begin{aligned} \pi_{ij}^{p+1} &= \left[\pi_{ij}^{p} + \frac{E_{ij}^{p+1} - E_{ij}^{p}}{E^{p}}\right]\frac{E^{p}}{E^{p+1}} \\ &= \left[\pi_{ij}^{p} + \frac{\triangle E_{ij}}{E^{p}}\right]\frac{E^{p}}{E^{p+1}}. \end{aligned} \tag{6}$$

In this expression, the initial period p employment share is added to the percentage change in employment for cell i, j. This sum is multiplied by a normalization term which accounts for total employment growth.

Let k denote worker flows between periods such that the sets E_{ijk} partition the sets E_{ij}. Then, $\triangle E_{ij} = \sum_{k} \triangle E_{ijk}$, where $\triangle E_{ijk}$ is the change in the total number employed in cell i, j from worker flow k. To compute counterfactual employment changes, I sequentially set employment changes to zero for each worker flow group. For example, the counterfactual employment for group $k = 1$ is computed as the change in employment shares when $\triangle E_{ij1} = 0, \forall\, i, j$ such that

$$\pi_{ij}^{p+1,C_1} = \left(\pi_{ij}^{p} + \frac{\sum_{k=2}^{6} \triangle E_{ijk}}{E^{p}}\right)\frac{E^{p}}{E^{p+1} - \sum_{i}\sum_{j}\triangle E_{ij1}}. \tag{7}$$

The final term of the expression re-normalizes the denominator to reflect counterfactual total em-

[26] Note that the weighted average share is simply the ratio of agreggate employments across LLMs as $\frac{1}{L}\sum_{l=1}^{L}\left[L\frac{E_{l}^{p}}{\sum_{l=1}^{L}E_{l}^{p}}\right]\frac{E_{ij}^{p}}{E_{l}^{p}} = \frac{\sum_{l=1}^{L}E_{ijl}^{p}}{\sum_{l=1}^{L}E_{l}^{p}}$.

ployment in the second period. The counterfactual change in correlation is then defined as:

$$\triangle\rho^{C_k} \quad = \quad \mathit{Corr}\left(\pi_{ij}^{p+1,C_k}\overline{\alpha}_i^{p+1}, \pi_{ij}^{p+1,C_k}\overline{\psi}_j^{p+1}\right) - \mathit{Corr}\left(\pi_{ij}^{p}\overline{\alpha}_i^{p}, \pi_{ij}^{p}\overline{\psi}_j^{p}\right). \tag{8}$$

The contribution of each worker flow component is then simply computed as:

$$\triangle\rho - \triangle\rho^{c_k}. \tag{9}$$

This decomposition method is a partial equilibrium exercise since I assume that changes in the employment distribution do not affect the average fixed effect values $\overline{\alpha}_i$ and $\overline{\psi}_j$ or any of the other worker flows. Although restrictive, this is a standard assumption in decompositions of this type (DiNardo et al., 1995; Oaxaca, 1973; Blinder, 1973).

This is a generalization of the Oaxaca-Blinder approach. In my case the correlation is a function of six employment flow variables and ten prices (i.e. the average fixed effect values within the quintiles). To draw the analogy, let f be a general function of these arguments. Let e_k represent a vector of employment levels of all cells of the joint WFE-EFE distribution and e_{-k} all worker flows except k. In general terms, the contribution of flow k is equal to:

$$f\left(e_k^{p+1}, e_{-k}^{p+1}, \overline{\alpha}_i^{p+1}, \overline{\psi}_j^{p+1}\right) - f\left(e_k^{p}, e_{-k}^{p+1}, \overline{\alpha}_i^{p+1}, \overline{\psi}_j^{p+1}\right). \tag{10}$$

Essentially, I am taking an empirical derivative by holding all variables constant expect for the variable of interest. However, since the function f is not separable in all its arguments, this answer may change depending on the level of the variables being held constant. In practice, however, the levels of the other variables make very small differences to the final answer. In addition to decomposing the total change into changes in worker flows, I also account for changes in average quintiles prices. However, these components turn out to be small.

To implement this approach I apply a simple regression framework. Although these components can be computed as basic descriptive statistics without this framework, this setup creates continuity when I apply the decomposition method to estimates of the effect of trade on sorting. I estimate many weighted least squares regressions of the form:

$$\frac{\triangle E_{ijkl}}{E_l^p} = a_{ijk} + \delta^p + \epsilon_{ijkl}^p \tag{11}$$

where a_{ijk} is simply the parameter of a constant and δ^p is a fixed effect for period p. The regressions are weighted by initial labor market employment E_l^p. Given this weighting, $\hat{a}_{ijk}$ is the average change in worker -flow-cell employment as a proportion of total initial employment, or $\frac{\triangle E_{ijk}}{E^p}$. The aggregate estimate for the cell $\hat{a}_{ij}$ is similarly equal to the average change in cell employment divided by total initial employment, or $\frac{\triangle E_{ij}}{E^p}$. Thus, $\hat{a}_{ij} = \sum_k \hat{a}_{ijk}$.

Using this notation the expression for lead employment in equation (6) can be written as:

$$\pi_{ij}^{p+1} = \left[\pi_{ij}^{p} + \sum_k \hat{a}_{ijk}\right] \frac{E^p}{E^{p+1}}. \quad (12)$$

Counterfactual estimates involve shutting down each $\hat{a}_{ijk}$ sequentially and re-normalizing total second period employment, E^{p+1}, as in equation (7).

This method of approximating the correlation of worker and firm effects through quintiles works quite well. For example, the change in average LLM correlation between the estimation intervals 1985 to 1991 and 1996 to 2000 is 0.141 whereas the approximation method detailed above delivers a change of 0.139. For the second period, the approximation also works well with a 0.169 change in the average LLM correlation and an estimated 0.186 change from the quintile method. Therefore, it appears that little information is lost by approximating the distribution with quintiles.

4.2 Results

Table 2 presents the results of the decomposition exercise of changes in sorting into the contributions of worker flow groups. I report the results separately for each period. Columns (1) through (4) present results for differences between the periods 1985 to 1991 and 1996 to 2002 and columns (5) through (8) for 1992 to 1996 and 2003 to 2009. For ease of exposition I refer to each period by its median year. For each period, the table is structured so that the first column, labeled E_k^p (%), presents the relative size of the worker flow group. The second column, labeled $\%\triangle E_k$, reports the growth in this flow relative to total initial employment. The third column, labeled $\triangle\rho_k$, reports the contribution of a given worker flow to sorting. The fourth column, labeled $\triangle\rho_k$ (%), reports the contribution of a given worker flow in relation to the total change in sorting.

The decomposition shows several interesting results. First, of the six worker flows, labor market entry is the most important determinant of increasing sorting across both periods. From 1988 to 1999, flows from net labor market entry throughout the fixed effect distribution were responsible for 62.2% of the total change. From 1993 to 2006, the corresponding number is 51.8%. These results represent the total effect of net labor market entry–potentially including a within- and a between-group component. The within-group component captures an effect in which labor market entrants are more sorted in their initial jobs than labor market exiters in their final jobs. The between group component is captured by differences in average WFE or EFEs between entrants and exiters.

The second most prominent channel is job stayers which comprises 12.7% and 12.9% of the to-

Table 2: Contribution of Net Worker Flows to Changes in Corr(EFE,WFE)

	I. Interval 1: '88 to '99				*II. Interval 2: '93 to '06*			
	E_k^p (%) (1)	$\%\triangle E_k$ (2)	$\triangle\rho_k$ (3)	$\triangle\rho_k$ (%) (4)	E_k^p (%) (5)	$\%\triangle E_k$ (6)	$\triangle\rho_k$ (7)	$\triangle\rho_k$ (%) (8)
Labor market entry	30.4	-0.5	0.094	62.2	36.5	-9.1	0.108	51.8
Between-LLM job-to-job	*15.1*	*0.0*	*0.015*	*9.8*	*15.9*	*0.1*	*0.030*	*14.5*
Within-LLM job-to-job	*15.2*	*0.0*	*0.005*	*3.4*	*15.0*	*0.0*	*0.017*	*7.9*
Job-to-job	30.3	0.0	0.020	13.2	30.9	0.1	0.047	22.4
Other to emp.	*9.1*	*2.1*	*0.012*	*8.3*	*10.9*	*-0.6*	*0.020*	*9.6*
Unemp. to emp.	*5.4*	*-3.7*	*0.004*	*2.5*	*2.8*	*-1.0*	*0.005*	*2.6*
Nonemployment	14.6	-1.7	0.016	10.8	13.7	-1.6	0.025	12.2
Job Stayers	24.7	0.0	0.019	12.7	18.9	0.0	0.027	12.9
Change quintile values			0.002	1.1			0.002	0.7

Notes: Estimates of contributions of worker flows to LLM sorting based on the methology of Section 4.1. "E_k^p (%)" presents the initial share of a given worker flow relative to total LLM employment. "$\%\triangle E_k$" presents the change in employment of a given worker flow divided by initial total LLM employment. "$\triangle\rho_k$" presents the component of the change in the correlation of worker and establishment fixed that can be attributed to a given worker flow. "$\triangle\rho_k$ (%)" presents the contribution of a given worker flow as a share of the total change in sorting. "$\triangle$ avg. quintile vals" presents the contribution of changes in average quintile values across the establishment and worker fixed effect distribution to the total change in sorting.

tal change in sorting in the first and second periods, respectively. This result suggests that changes in EFEs and WFEs are correlated with initial fixed effect levels. Therefore, contrary to the perception that sorting reflect movements of workers across firms and employment states, a measure of sorting based on the AKM methodology can increase when workers stay at the same firms.

Between-LLM job-to-job transitions also account for significant share of the total change in sorting–estimated at 9.8% and 14.5% for the two respective periods. Within-region reallocation appears to play a minor role–accounting for 3.4% and 7.9% in the two respective periods. Another important source of sorting is movements between other and employment. This channel accounts for 8.3% of the total effect from 1988 to 1999 and 9.6% from 1993 to 2006. These results suggest that over time workers hired out of "other" are more sorted that those exiting employment to "other". Although, this channel may identify individuals out of the labor force, these movements may also be job-to-job transitions from part-time, non-Social-Security-covered employment, or employment in East Germany. Adding the share from "other" to the shares from job-to-job transitions provides an upper bound for reallocation. The respective upper bounds in each period are 21.5% and 32.0%. The total effect of reallocation, therefore, although significant, is not the dominant force driving increases in sorting.

Net flows from unemployment to employment are responsible for a small share of the total change in sorting with 2.5% in the first period and 2.6% in the second. This result suggests that the firm that rehires an unemployed worker is similar to the firm that initially displaced her. Thus, this prominent labor market flow does not greatly affect sorting. This is partly due to the fact that unemployment transitions make up a small share of total worker flows.

Despite the fact that the AKM regression controls for returns to experience, there is a tendency for workers to move up the WFE distribution when they stay employed for consecutive periods. Therefore, if young workers enter with low WFE's in low EFE firms and subsequently move up both the WFE and EFE distribution over time, then the contribution of net labor market entry will include a life-cycle effect. In this case, comparing the net flows of exiters minus entrants may exaggerate the role labor market entry. For instance, suppose sorting remains unchanged between two periods, yet workers follow the life-cycle pattern described above. Then the total change in sorting is zero, but net labor market entry will report a positive contribution due to the life-cycle effect. Since the total effect sums to zero, other flows must reflect negative contributions. If this life-cycle effect is large, it can potentially complicate the interpretation of the aggregate results.

One way to remove the life-cycle component is to compare the contribution of net labor market entry across LLMs experiencing different rates of change in sorting. Assuming that the life-cycle effect is uncorrelated with the rate of change of sorting in a LLM will identify changes in sorting due only to differences in entry. This provides another reason to study the effect of trade on sorting. By comparing responses of different LLMs to trade shocks, the life-cycle effect is differenced out.

5 The Impact of Trade Shocks on Labor Market Sorting

As documented in Dauth et al. (2014), Germany experienced a surge in trade flows to and from both Eastern Europe and China from 1990 to 2010. The growth in trade corresponds to the opening of China and the fall of the Soviet Union in Eastern Europe. Both of these events can be viewed as largely exogenous to domestic German industry and, therefore, serve as useful shocks to analyze the effects of trade. In additional to their initial openings, both of these regions joined the WTO around 2001 which led to a further economic integration.

5.1 Methods

The work of Autor et al. (2013) has become influential in the study of trade on local labor markets (LLMs) and I largely follow their methodology. I construct a Bartik-style measure of regional export exposure per worker by assigning national changes in industry exports to local labor markets based on their initial share of industry employment:

$$\triangle EXP_{lt}^{GER} = \sum_{s} \frac{E_{lst}}{E_{st}} \frac{\triangle EXP_{st}^{GER \rightarrow EAST}}{E_{lt}}. \tag{13}$$

$\triangle EXP_{st}^{EAST}$ denotes the observed change in national exports from Germany to the East between time period t and $t+1$ in industry s. E_{lt} is total employment in region l in period t. E_{lst}/E_{st} is the share of national employment of industry s employed in region l in initial period t. I create a measure of import exposure $\triangle IMP_{st}$ with the corresponding equation using national imports.

Although the opening of the East to trade can be viewed as exogenous to domestic industry at the moment of initiation, the gradual and continuous nature of this process warrants the use of an additional instrument to disentangle potentially endogenous supply and demand factors emerging over time. In other words, over short periods of time around the initial opening to trade and accession to the WTO, we may expect trade flows from the East to be exogenous across industries in the domestic German market. However, over time industries may evolve such that trade flows represent endogenous industry supply differences. For example, suppose that the German car industry innovates successfully to capture global market share. Differences in industry trade flows to the East will in part reflect these innovations of the car industry, rather than the pure demand effects of market access.

To alleviate concerns over endogeneity, I follow Autor et al. (2013) and Dauth et al. (2014) by constructing an instrument based on trade flows to nine comparably developed countries which are not members of the European Monetary Union:

$$\triangle EXP_{lt}^{Other} = \sum_{s} \frac{E_{ls,t-1}}{E_{s,t-1}} \frac{\triangle EXP_{st}^{Other \to EAST}}{E_{l,t-1}}. \tag{14}$$

In addition the trade flows to other countries, the instrument varies from the measure of trade exposure as employment levels are measured with ten year lags. The countries upon which the instrument is constructed are Australia, Canada, Japan, Norway, New Zealand, Sweden, Singapore, and the United Kingdom. In the case of exports shocks, the instrument is constructed to isolate the effect of foreign demand from domestic supply. Using variation based on goods that many other developed countries buy from and sell to the East, removes idiosyncratic Germany supply and demand components. The instrument is based on lagged industry employment shares to alleviate the concern that some industries could anticipate high returns from Eastern market access and, therefore, mobilized ahead of time.

I follow Dauth et al. (2014) and Autor et al. (2013) in analyzing the effect of export and import shocks on local labor market outcomes by estimating the following equation:

$$\triangle y_{lt} = \beta_1 \triangle EXP_{lt} + \beta_2 \triangle IMP_{lt} + \gamma X_{lt} + \lambda_{r(l)} + \delta_t + \epsilon_{lt} \tag{15}$$

where y_{it} represents a labor market outcome of local labor market l in time period t, X_{lt} represents initial labor market characteristics of a region, $\lambda_{r(l)}$ represents a region fixed effect in which $r(l)$ denotes a function from counties to larger geographic regions, and δ_t captures a time period fixed effect. Since the regression is performed in changes, the fixed effects capture common trends rather than levels. Changes are denoted as $\triangle$, such that $\triangle y_{lt} = y_{lt+1} - y_{lt}$.

5.2 Results on Employment and Wages

Prior to presenting the main results of the effect of trade on sorting, I present evidence that trade indeed acts as a demand shock to the affected industries. Conceptually the idea is that trade works through demand to induce sorting. Although I have no direct measure of demand, I present evidence on the effect of trade on manufacturing employment and wages.

Table 3 presents the results of estimating equation (15) with four separate dependent variables. The first column estimates the effect of trade shocks on manufacturing employment. Export exposure significantly increases employment with a coefficient of 1.358 log points. At the mean level of export exposure, this represents a 5.4% increase in manufacturing employment. Import exposure results in a similar decline of employment. Wages, on the other hand, are a different story. Export exposure is estimated to increases wages by 0.334 log points while there is an insignificant decline in wages from import exposure. At the mean level of export exposure, this represents

1.3% increase in manufacturing wages. An increase in employment coupled with rising wages is indicative a shift upward in demand for manufacturing labor. Thus, I interpret export shocks as increasing labor demand via product demand.

Columns (3) and (4) represent the establishment fixed effect (EFE) and worker fixed effect (WFE) components of wages, respectively. While neither, component is significant for imports, export exposure leads to an increase in the average level of WFEs for workers employed in manufacturing firms. Therefore, on average, the increase in wages is realized through an change in composition rather than an increase in the firm wage premium.

Table 3: 2SLS Results of Employment and Wages on Trade Shocks

	△ Emp (1)	△ Wage (2)	△ EFE (3)	△ WFE (4)
Export exposure	1.358***	0.334**	-0.072	0.435***
	(0.430)	(0.160)	(0.157)	(0.116)
Import exposure	-1.519***	-0.098	0.000	-0.042
	(0.585)	(0.230)	(0.126)	(0.180)
Labor market controls	Y	Y	Y	Y
# geo f.e.'s	214	214	214	214
Adj R^2	0.711	0.599	0.995	0.993
N (county-periods)	650	650	650	650

Notes: All 2SLS regressions are weighted by the initial size of the regional labor force. Standard errors are clustered at the LMR2 level. Labor market controls include: initial level of sorting, % employment in manufacturing, % high skilled, % foreign born, % female, and % routine occupation.

5.3 Results on Sorting

My primary outcome of interest is the correlation of EFEs and WFEs within a LLM. As fixed effects represent a component of wages, an increase in the correlation of the two components represents an increase in inequality as high wage establishments are more likely to employee high wage workers.

Table 4 presents estimates of the causal effect of trade shocks on male labor market sorting. I estimate equation (15) with multiple specifications, primarily varying the geographic fixed effect. Column (1) presents the OLS estimates which indicate that export exposure shocks intensify sorting whereas import shocks have the opposite effect. The magnitude of the effect of export exposure is larger and is estimated with smaller standard errors. All regressions are weighted

Table 4: 2SLS Results of Sorting on Trade Shocks for Males

	Region fixed effect					
	OLS: None (1)	IV: None (2)	IV: State (3)	IV: LMR1 (4)	IV: LMR2 (5)	IV: LMR2 (6)
Export exposure	0.0093*** (0.0022)	0.0131*** (0.0029)	0.0109*** (0.0033)	0.0120*** (0.0028)	0.0118*** (0.0029)	0.0080*** (0.0025)
Import exposure	-0.0028 (0.0025)	-0.0082* (0.0042)	-0.0047 (0.0043)	-0.0045 (0.0046)	-0.0020 (0.0055)	-0.0014 (0.0050)
Initial sorting						-0.6185*** (0.0050)
Labor market controls	N	N	Y	Y	Y	Y
# geo fixed effects	0	0	11	74	214	214
Adj R^2	0.093	0.076	0.115	0.212	0.278	0.445
N (county-periods)	650	650	650	650	650	650

Notes: All 2SLS regressions are weighted by the initial size of the regional labor force. Standard errors are clustered at the LMR2 level. Labor market controls include: % employment in manufacturing, % high skilled, % foreign born, % female, and % routine occupation.

by initial county employment so that the results represent average worker-weighted effects across LLMs. Column (2) presents IV estimates without controls. Column (3) adds controls for state trends in sorting. Following Autor et al. (2013) and Dauth et al. (2014), I also include controls for the initial characteristics of the labor market including: percentage of employment in manufacturing, percentage of high skilled employment, percentage of foreign born employment, percentage of female employment, and percentage of routine occupation employment. These controls reduce the magnitude of both coefficients and remove any statistical significance from the import coefficient. The export coefficient, however, remains highly significant.

Columns (4), (5), and (6) use a taxonomy of labor market regions produced by Dustmann and Glitz (2015) denoted as *LMR1* and *LMR2*, respectively. The variation in labor market outcomes is at the county level of which there 325 in West Germany. LMR1 and LMR2 represent broader definitions of labor markets which resemble commuting zones in the US. There are 74 LMR1s and 214 LMR2s in West Germany. A potential concern is that the estimates reflect long-term industry trends rather than the changes in terms of trade with the East. If the geographic concentration of industries is stable, then using within-region variation over time alleviates these concerns. As the geographic fixed effects become narrower, the estimates use less cross-sectional variation and produce a more conservative test.

The export coefficient stays stable as successively less variation is used. The import coefficient, however, declines significantly and loses statistical significance. Column (6) add a control for the initial level of labor market sorting. This variable is significant and reduces the export coefficient slightly. As the most conservative specification, Column (6) represents the main specification for the analysis. Appendix Table A2 shows that similar results hold for women.[27]

The economic magnitude of the export coefficient is significant. Multiplying the export and import coefficients of Column (6) by the average change in trade exposure over the period 1988 to 2008, the total predicted change in the correlation is 0.0392.[28] The total change in average within-LLM sorting over the sample period is 0.229.[29] The predicted change represents 17.1% of the total change in sorting. However, following Autor et al. (2013) I use a more conservative estimate the total change in trade. Given that the estimated effect is with respect to the exogenous change in trade, I use only the proportion the variation in trade exposure explained by the instrument. This allows for the possibility that endogenous changes in trade flows do not have an effect on sorting. Therefore, I estimate that trade with the East is responsible for 0.0326 or 14.2% of the total change in West Germany sorting.[30]

6 Decomposition of the Effect of Trade on Sorting into Worker Flows

6.1 Methods

To decompose the effect of trade on sorting into worker flow channels I follow a similar method as described in Section 4.1. However, instead of running a simple regression to compute the average change in employment cells as in equation (11), I estimate the full trade model of equation (15). I estimate the effect of trade shocks on employment changes throughout the joint WFE-EFE distribution:

$$\frac{\triangle E_{ijkl}}{E_l^p} = \beta_1^{ijk} \triangle EXP_{lt} + \beta_2^{ijk} \triangle IMP_{lt} + \gamma^{ijk} X_{lt} + \lambda_{r(l)}^{ijk} + \delta_t^{ijk} + \epsilon_{lt}^{ijk}. \tag{16}$$

The dependent variable in equation (16) is the change in employment in WFE-EFE cell ij, worker flow k, and LLM l divided by total initial employment in LLM l. It therefore represents the change in a given employment cell as a share of total initial LLM employment. This equation is estimated by two-stage least squares using the same instrument as described in Section 5.1. Similar

[27] Add robustness results for separate intervals and differences between Eastern Europe and China.

[28] The employment weighted average change in exports (imports) is 7.61 (6.25) from 1988 to 2008. Therefore, 7.62*0.0080-6.25*0.0014=0.0522. Given that the intervals overlap I think multiply by 0.75 to get 0.0392

[29] See Table 1.

[30] For exports the ratio of instrument to total variation is 0.83, for imports 0.82. Therefore, the calculation becomes 0.75(7.62*0.0080*0.83-6.25*0.0014*0.82)=0.0326.

to equation (12) I compute the total change in employment due to export shocks as:

$$\pi_{ij}^{p+1} = \left[\pi_{ij}^{p} + \sum_k \hat{\beta}_1^{ijk}\right] \frac{E^p}{E^p + \hat{\beta}_1} \tag{17}$$

where $\hat{\beta}_1 = \sum_k \sum_i \sum_j \hat{\beta}_1^{ijk}$. Counterfactual distributions are computed by shutting down the worker flow channels of trade, $\hat{\beta}_1^{ijk}$, sequentially and adjusting the denominator of the population adjustment factor appropriately.

The approximation to quintiles works well in this case also. The decomposition method yields an total change in sorting due to exports of 0.0093. This is similar to the regression coefficient of 0.0080.

6.2 Worker Flows

Table 5 presents the results of a decomposition of the effect of export exposure on sorting into worker flow channels. Panel I presents the results of the worker flow decomposition. Column (1), labeled $\triangle\rho_k$, presents the contribution of a given flow to changes in sorting. Column (2), labeled $\triangle\rho_k$ (%), presents the worker flow contribution as a percentage of the total change. Panel II presents a picture of the size of each worker flow channel. Column (3), labeled E_k^p (%), presents the initial share of a given worker flow as a percentage of total initial employment. Column (4), labeled $\%\triangle E_k$, presents an estimate of the export-induced change in employment of a given worker flow as a percentage of total initial employment. Panel III takes an average of the worker flow share contributions from Table 2.

Turing to the results in Panel I, we see that once again the most important contributor to increased sorting is flows into and out the labor market. Net labor market entry alone comprises 47.7% of the total effect of exports on sorting. This net effect is smaller than the contribution to the aggregate effect of sorting. This is consistent with the idea that some portion of the net labor market entry share of the aggregate sorting change is due to a life-cycle component. However, this component is not large enough to change the general conclusion that worker flows into employment from labor market entrants are the most significant contributors to changes in LLM sorting.

Job stayers comprise the second most important flow–contributing 25.0% of the total export effect. This result suggests that demand shocks, at least when targeted toward manufacturing firms, produce increases in wage components that are correlated with the initial WFE-EFE distribution.

Reallocation is also a significant contributor to sorting as job-to-job transitions account for 16.6% of the total effect. Interestingly, within-LLM reallocations account for none of the total effect as it is all driven by between-LLM job switching. Net flows into and out of the other

Table 5: Decomposition of Export Sorting into Worker Flows

	I. Components of Change in Sorting through Exports		*II. Employment Shares*		*III. Components of Change in Aggregate Sorting*
	$\triangle\rho_k$ (1)	$\triangle\rho_k$ (%) (2)	E_k^p (%) (3)	$\%\triangle E_k$ (4)	$\triangle\rho_k$ (%) (5)
Labor market entry	0.0045	47.7	33.5	0.35	57.0
Between-LLM job-to-job	*0.0016*	*16.6*	*15.5*	*0.18*	*12.1*
Within-LLM job-to-job	*0.0000*	*0.0*	*15.1*	*0.00*	*5.7*
Job-to-job	0.0016	16.6	30.6	0.18	17.8
Other to emp.	*0.0009*	*9.8*	*10.0*	*0.20*	*8.9*
Unemp. to emp.	*0.0000*	*0.3*	*4.1*	*0.17*	*2.6*
Nonemployment	0.0009	10.1	14.1	0.37	11.5
Job Stayers	0.0023	25.0	21.8	0.00	12.8

Notes: Estimates of contributions of worker flows to export-induced LLM sorting based on the methology of Section 6.1. "$\triangle\rho_k$" presents the component of the change in the correlation of worker and establishment fixed that can be attributed to a given worker flow through export exposure. "$\triangle\rho_k$ (%)" presents the contribution of a given worker flow as a share of the total export-induced change in sorting. "E_k^p (%)" presents the initial share of a given worker flow relative to total LLM employment. "$\%\triangle E_k$" presents estiamtes of the *export-induced* change in employment of a given worker flow divided by initial total LLM employment.

category are also a significant contributor to sorting–accounting for 9.8% of the total export effect. The total contribution of reallocation can be bounded at 26.4%. Thus, at most, about a quarter of the increase in sorting following export shocks are driven by job-to-job transitions.

A striking result emerges through a comparison of the trade-induced sorting flows with the aggregate sorting flows. Column (5) presents the average contribution of each worker flow as a percentage of the total change in sorting across both periods. The aggregate shares are quite similar to the trade shares. The main differences are that net labor market entry is slightly less important in the trade flows and both between-LLM reallocation and job stayers are slightly more important. These results suggest that increases in demand from other sources, whether domestic or international, have the potential to explain a larger share of the total change in sorting than the direct effect of trade from the East alone.

7 Export-Induced Worker Flows by Industry and Firm Type

7.1 Connection of Results to Trade Theory

Despite its simple form, it is difficult to incorporate all the features of the AKM empirical structure into a theoretical model. The existence of firm fixed effects requires a departure from perfect competition in the labor market to allow for the possibility that similar workers are paid differently depending on their place of work. Variance in firm premiums requires a source of firm heterogeneity. A common approach used to incorporate firm heterogeneity is to allow heterogeneity in productivity and monopolistic competition in the product market. Finally, variance in worker fixed effects requires heterogeneity in worker productivity. All told a theoretical model would require productive heterogeneity on both the firm and worker side as well as imperfect market competition in both the product and labor market. To the best of my knowledge, no current trade model is able to incorporate all of these features.

Trade models of within-industry firm heterogeneity typically abstract from modeling the interactions of geographic- and industry-specific labor markets. Given that I measure the full effects of local labor market (LLM) and manufacturing sector specific export shocks, I allow for the possibility of between-LLM and between-industry reallocation.[31] These channels provide alternative margins of adjustment which are important to consider when applying the predictions of the trade literature to the results.

In lieu of a fully specified trade model that is consistent with the AKM structure, I briefly describe some important predictions of the recent trade literature to guide the interpretation of the subsequent results. The model of Melitz (2003) has become influential in the study of international

[31] Autor et al. (2013) find strong wage effects in the non-manufacturing sector as a result of the China import shock in US LLMs.

trade through its treatment of firm heterogeneity in productivity. A key prediction of this model is that trade liberalization disproportionately benefits the most productive firms as increases in demand accentuate productivity differences. As top firms bid up the price of labor, wages rise for all firms. As a result the least productive firms exit. In the end, market share is reallocated from the least to most productive firms–raising aggregate efficiency. Note that despite the fact that the trade shock is common across the industry, heterogeneous responses impact within-industry variation in productivity.

Sampson (2014) extends the Melitz (2003) model by allowing for worker heterogeneity in skill and endogenous technological choice on the firm side. By incorporating heterogeneity on both sides of the labor market, Sampson (2014) connects the literature on assortative matching to a trade context. An assumption of complementaries in the production function leads to positive assortative matching–a standard result. Trade liberalization has similar implications as in the Melitz (2003) model, as the most productive firms profit most. However, is this case dispersion in firm productivity leads to dispersion in worker wages. Since top workers work at top firms, marginal product of labor increases more for high type workers and hence wage inequality increases. If firms can choose their optimal level of technological investment, trade liberalization induces firms to upgrade technology. Given a closed labor market, however, the matching of firms and workers is constant. Extending the model to allow firms to hire workers from other industries or regions could change this result. Both demand shocks and technological upgrading would provide an incentive for firms to upgrade the quality of their workforce.

Some predictions broadly consistent with this strand of the trade literature are as follows.[32] The most productive manufacturing firms benefit the most from export exposure. Given the presence of between-industry and between-region margins of adjustment, top manufacturing firms also upgrade the quality of their workforce. Furthermore, manufacturing firms increase technological investment as a result of trade liberalization to fully exploit their revenue potential. Insofar as technology is complementary with high-skill labor and a substitute for low-skill labor, we expect a relative reduction of low-skill labor in manufacturing firms as a result of demand increases.

7.2 Export Flows by Industry

In order to clarify the effects of the export shock I classify firms into broad industry sectors: manufacturing and non-manufacturing. Table 6 presents the results of the decomposition of the effect of trade on sorting into work flows by sector. Panel I presents the results of a decomposition while panel II shows the initial employment shares and the estimated total change in employment for a

[32] I am considering the case in which the rise of the East acts as either an inrease in trading partners or decrease in the variable costs of trade. Reductions in the fixed costs of trade will have subtely different predictions. See Melitz (2003) and Sampson (2014) for a discussion of the comparative statics.

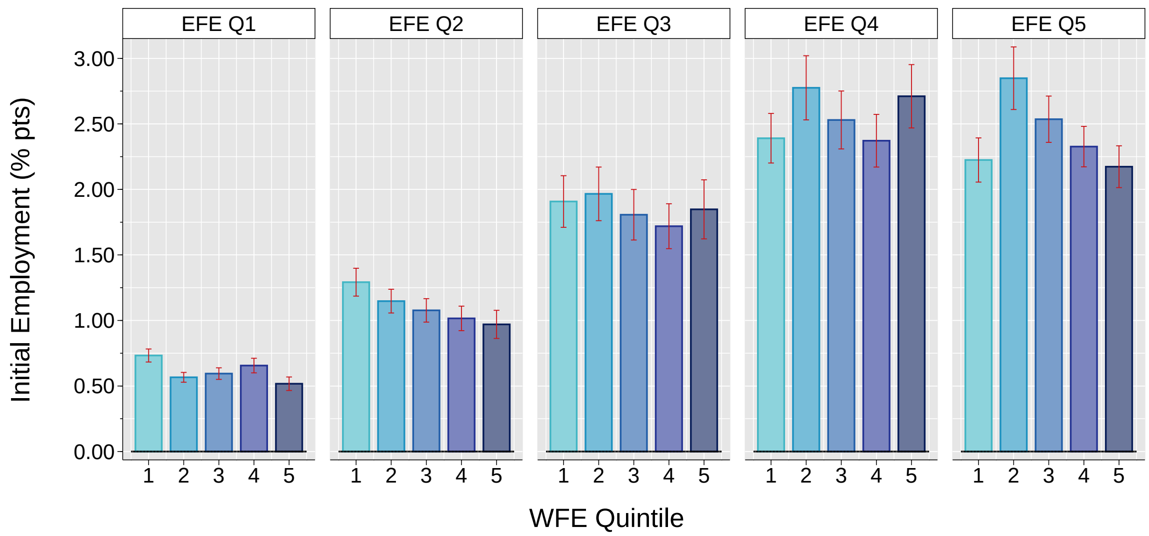
Table 6: Decomposition of Export Sorting into Worker Flows by Industry

	I. Components of Change in Sorting through Exports				*II. Employment Shares*			
	Manufacturing		Non-Manufacturing		Manufacturing		Non-Manufacturing	
	$\triangle\rho_k$ (1)	$\triangle\rho_k$ (%) (2)	$\triangle\rho_k$ (3)	$\triangle\rho_k$ (%) (4)	E_k^p (%) (5)	$\%\triangle E_k$ (6)	E_k^p (%) (7)	$\%\triangle E_k$ (8)
Labor market entry	0.0002	2.4	0.0042	45.7	13.7	-0.14	19.8	0.49***
Between-LLM job-to-job	*0.0008*	*8.4*	*0.0008*	*8.3*	*5.5*	*0.18****	*9.9*	*0.00*
Within-LLM job-to-job	*0.0003*	*3.1*	*-0.0003*	*-3.1*	*6.6*	*0.00*	*8.5*	*0.00*
Job-to-job	0.0011	11.5	0.0005	5.2	12.1	0.18	18.5	0.00
Other to emp.	*0.0007*	*8.0*	*0.0002*	*1.9*	*3.4*	*0.13*	*6.5*	*0.07*
Unemp. to emp.	*-0.0002*	*-2.1*	*0.0002*	*2.4*	*1.9*	*0.20****	*2.3*	*-0.04***
Nonemployment to emp.	0.0005	5.8	0.0004	4.3	5.3	0.33	8.8	0.04
Job Stayers	0.0029	30.7	-0.0005	-5.6	11.6	0.00	10.2	0.00
Industry total	0.0047	50.5	0.0046	49.5	42.7	0.37	57.3	0.52

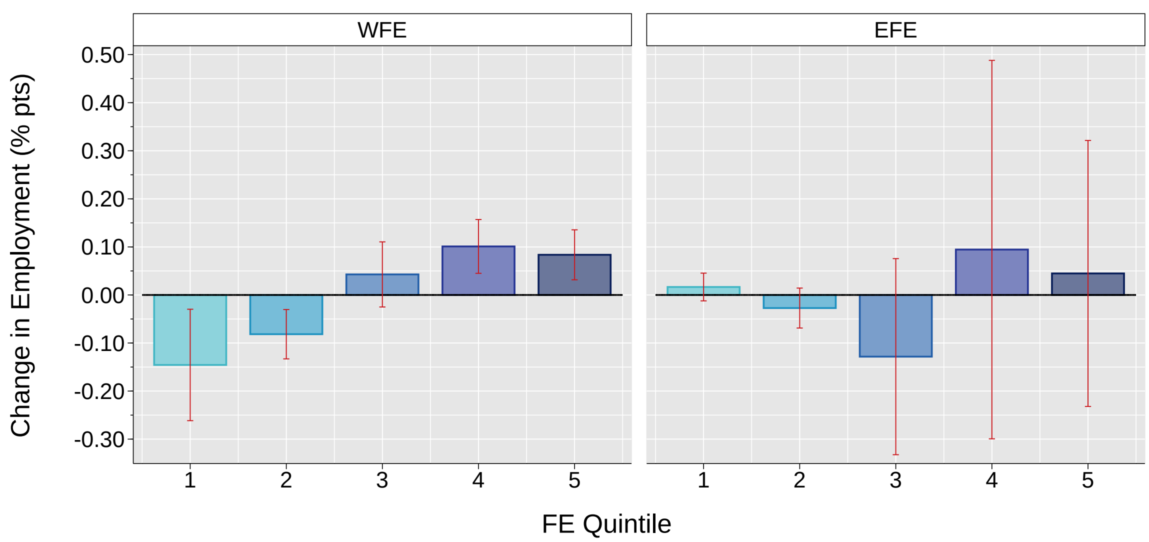
Notes: Estimates of contributions of worker flows to export-induced LLM sorting based on the methology of Section 6.1. "$\triangle\rho_k$" presents the component of the change in the correlation of worker and establishment fixed that can be attributed to a given worker flow through export exposure. "$\triangle\rho_k$ (%)" presents the contribution of a given worker flow as a share of the total export-induced change in sorting. "E_k^p (%)" presents the initial share of a given worker flow relative to total LLM employment. "$\%\triangle E_k$" presents estiamtes of the *export-induced* change in employment of a given worker flow divided by initial total LLM employment.

Figure 1: Amplification in the Manufacturing Sector

(a) Initial Joint WFE-EFE Distribution of Manufacturing Jobs



(b) Export-Induced Changes in FEs for Job Stayers in Manufacturing Firms



Notes: Red brackets represent 90% confidence intervals. Subfigure (a) plot the intial distribution of manufacturing employment across the joint WFE-EFE distribution by taking an average of the intial distributions of both periods of change: '88 to '99 and '93 to '06. Subfigure (b) presents the estimated coefficients from equation (15) using total employment changes in each quintile of the marginal EFE and WFE distributions divided by initial total LLM employment.

given worker flow group.

A striking result is that all of the effect of net labor market entry works through the non-manufacturing sector. The first row of column (2) shows that changes in net labor market entry patterns into manufacturing firms explain only 2.4% of the total export effect. On the other hand, changes in net labor market entry into the non-manufacturing sector are responsible for 45.7% of the total change in export-induced sorting. This is despite the fact that these flows comprise only 20% of the initial employment distribution (column (7)). Furthermore, comparing columns (6) and (8) we can see a difference in the total flows accruing to each sector. Entrants to export exposed LLMs are significantly *less* likely to enter the manufacturing sector and *more* likely to enter the non-manufacturing sector. The net effect is insignificantly different from zero. Therefore, entrants are not in general more likely to enter the labor market in export exposed LLMs, but there is a significant switch away from the manufacturing sector despite the positive demand shock.

Another interesting result is a stark divergence in the effect of job stayers on sorting in the manufacturing versus the non-manufacturing sector. The effect of job stayers is fully accounted for through the manufacturing sector. In fact the effect of job stayers on sorting in non-manufacturing firms is slightly negative. In so far as amplification is the result of increases in within-type fixed effects, the result that amplification works mainly through the manufacturing sector is consistent with expectations. After all, the direct effect of the export-induced demand shock is to the manufacturing sector. Figure 1 presents a visual representation of amplification in the manufacturing sector. Subfigure 1a shows the initial distribution of manufacturing jobs. Each panel represents the share of total LLM employment in each EFE quintile across the range of WFE quintiles. Manufacturing jobs are disproportionately represented in the top two quintiles of the EFE distribution. Subfigure 1b reports estimated coefficients of the effect increases in export exposure on change in employment across the marginal distributions of WFE and EFEs. Export-induced demand shocks tend to increase WFEs but not EFEs. Therefore, these results combine to offer a picture of amplification in which jobs with initially high EFEs respond to demand shocks in export-exposed LLMs through increases in WFEs.

The result that demand shockss lead to increases in WFEs of jobs stayers suggests manufacturing workers receive a wage increase that is portable across industries. This result is consistent with a competitive labor market in which the skill of manufacturing workers are substitutable across industries. This result may stem from the fact that the LLM demand shock is derived from a national industry shock. We may expect the firm specific component of wages, the EFE, to play a larger role with firm- or region-specific shocks.

In contrast to the story for labor market entry and amplification, the industry effects of between-region reallocation are roughly equal. Column (2) shows that between-LLM job-to-job transitions account for 8.4% of the total effect. Column (4) shows that regional reallocations in the non-manufacturing sector account for 8.3%. Adding net "other" and net within-LLM flows produces an upper bound of 19.5% for manufacturing reallocation and 7.1% for non-manufacturing reallocation.

Columns (2) and (4) of the final row report the total contribution of each industry to export-induced sorting. At 50.5% for manufacturing versus 49.5% for non-manufacturing, the share are roughly equal. Given that the decomposition method aggregates between- and within-industry effects, it remains unclear which if these effects arise due to within-industry sorting. As previously noted, the literature emphasizes how export exposure can lead to within-industry dispersion in productivity which can lead to within-industry wage dispersion. To test whether this industry components represent within-industry sorting effects, I estimate the trade exposure equation (15) but instead use within-industry/within-LLM correlation of fixed effects as the dependent variable. Using the main specification, I estimate a coefficient on the effect of export exposure on within-manufacturing industry sorting of 0.0083 with a standard error of 0.0050 which is statistically significant at the 10% level. Although not as precisely estimated as the aggregate coefficient, this result provides evidence consistent with a view that industry demand shocks cause within-industry sorting. Furthermore, the magnitude of the coefficient is very similar to the aggregate coefficient. For the non-manufacturing industry, I estimate a positive, but statistically insignificant coefficient of export exposure on within-non-manufacturing sorting of 0.0041. This suggests that the effects of the non-manufacturing industry on export sorting are mostly between-industry effects.

7.3 Export Flows by Firm Type

Guided by trade theory, I analyze the results of export shocks on the sorting components across the EFE and initial firm size distributions. I use both EFEs and firm size as a proxy from firm productivity. Firm size is a measure which is correlated with productivity in many search and trade models. Section 3 provides evidence that EFEs are positively correlated with measures of firm productivity in a variety of settings.

The simplicity of my decomposition method allows it to flexibly cover a wide range of potential counterfactuals. In theory, I can estimate the effect of changes in each cell of the WFE, EFE, worker flow, and industry distribution on the total change in sorting. In the subsequent analysis, I decompose the contribution of worker flows at different points in the EFE distribution. Specifically, I compute separate counterfactual shares for three firm groups: low-, mid-, and high-EFEs.[33] This exercise provides a picture of the location in the joint distribution by which each flow affects sorting. For instance, a large share for the low-EFE group means that a change in employment for low-EFE firms increased sorting. In order for low-EFE firms to increase sorting it must be the case

[33] Low corresponds to the first two quintiles of the EFE distribution, mid corresponds to the third quintile, and high corresponds to the fourth and fifth quintiles.

that they gained relatively more low-WFE workers.

In order to provide a more complete picture of within-industry reactions to export shocks, I also condition by the size of the firm in the initial period. Within each LLM and sector, I compute worker-weighted firm size medians. I categorize firms as either small continuing, large continuing, or non-continuing firms. Non-continuing firms refer to establishments that either exited or entered the sample from the initial period to the lead period. This category is meant to capture the net effect of new firms. However, this category includes establishments that change ownership or simply were not included in the 2% sample in both periods.[34] Although some new firms may be highly productivity, on average I expect this group to be of lower productivity. Consistent with this view, non-continuing firms have lower average EFEs. Large firms are establishments which where in the top half of the firm size distribution in the initial period and appear in both periods. In terms of employment, the size bins initially have equal employment. Large firms are more likely to survive, however, and as a result make up a larger share of the employment distribution.

Table 7: Decomposition of Export Sorting into Worker Flows by Industry and Establishment Fixed Effect

	I. Share of Change in Sorting through Exports by Industry & EFE Distribution						*II. Initial Employment Shares by Industry & EFE Distribution*					
	Manufacturing			Non-Manufacturing			Manufacturing			Non-Manufacturing		
	Low (1)	Mid (2)	High (3)	Low (4)	Mid (5)	High (6)	Low (7)	Mid (8)	High (9)	Low (10)	Mid (11)	High (12)
Labor market entry	2.9	-3.8	3.2	32.8	1.1	11.8	2.7	2.9	8.1	10.6	3.7	5.5
Between-LLM job-to-job	*0.2*	*-0.5*	*8.7*	*13.9*	*0.1*	*-5.8*	*1.3*	*1.2*	*3.0*	*5.3*	*1.8*	*2.9*
Within-LLM job-to-job	*1.0*	*-0.5*	*2.6*	*-6.3*	*-0.4*	*3.6*	*1.4*	*1.5*	*3.7*	*4.8*	*1.6*	*2.1*
Job-to-job	1.3	-1.0	11.3	7.7	-0.3	-2.2	2.8	2.7	6.7	10.0	3.4	5.0
Other to emp.	*1.3*	*-0.5*	*7.2*	*9.5*	*-0.1*	*-7.5*	*0.9*	*0.7*	*1.8*	*3.8*	*1.1*	*1.6*
Unemp. to emp.	*-0.2*	*-0.4*	*-1.5*	*1.2*	*0.2*	*1.0*	*0.4*	*0.4*	*1.0*	*1.2*	*0.4*	*0.6*
Nonemployment to emp.	1.1	-0.9	5.7	10.7	0.2	-6.5	1.3	1.1	2.8	5.1	1.5	2.3
Job Stayers	-0.2	1.9	29.1	-3.3	1.1	-3.4	1.8	2.5	7.2	5.5	2.1	2.7
Industry total	5.1	-3.8	49.2	47.9	2.0	-0.3	8.6	9.2	24.9	31.1	10.7	15.5

Notes: Estimates of contributions of worker flows to export-induced LLM sorting based on the methology of Section 6.1. Panel I presents the contribution of a given worker flow as a share of the total export-induced change in sorting. Panel II presents the initial share of a given worker flow relative to total LLM employment. "Low" refers to employment in the first and second quintiles of the marginal EFE distribution. "Mid" refers to the third quintle. "High" refers to the fourth and fifth quintiles.

[34] Using the 100% BHP sample, Hethey and Schmieder (2010) find that around 20% of employment of entering and exiting establishments is due to establishment ID changes, spin-offs, or takeovers.

7.3.1 Effects on the Manufacturing Sector

Table 7 presents the worker flow decomposition results by industry across the marginal EFE distribution. I begin with a discussion of the results in the manufacturing sector. The most significant worker flow of the manufacturing sector is amplification. Column (3) makes clear that amplification affects the top end of the firm effect distribution. In fact, the effects of amplification are fully accounted for by the changes in employment of firms in the top two quintiles of the EFE distribution. This confirms the result that amplification produces more employment of high-WFE workers in high-EFE firms.

The other source of increasing manufacturing sorting comes from between-LLM reallocation. Similar to amplification, job-to-job transitions affect sorting at the top end of the joint distribution as high-EFE firms account for 8.7% of a total 8.4%. In response to export-induced demand shocks, top manufacturing firms engage in a modest reallocation of their workforce towards high-WFE workers. Other to employment movements are also concentrated at the top end of the joint distribution and show a similarity to between-LLM reallocation. For instance, for both flows the dominant source of sorting is employment changes at high-EFE firms. In contrast, low-EFE firms make the largest relative contribution in terms of unemployment flows. This pattern is repeated in reverse for the non-manufacturing sector. This suggests that the reallocation component of other to employment transitions is more important that the out of the labor force component which I expect to behave similarly to unemployment transitions.

Panel II shows that employment in the manufacturing sector is initially more concentrated in the upper end of the firm fixed effect distribution. For instance, employment in high-EFE firms accounts for 24.9% of initial LLM employment and 58.3% of initial manufacturing employment. However, this over-representation of employment at the top end cannot entirely explain the sorting results. Although 58.3% of initial manufacturing employment is concentrated in high EFE firms, changes in employment in these firms account for 97.4% of the total sorting effect of the manufacturing sector.[35]

Table 8 presents the results of the decomposition by industry and firm size. Panel I shows that employment changes of large firms are the dominant source of sorting. Large firms fully account for amplification and account for a majority of both between-LLM reallocation and other to employment flows. Panel II shows that large, surviving manufacturing firms account for 20.6% of total LLM employment and 46.9% of manufacturing employment. Still, they contribute a disproportionate share to sorting–accounting for 39.9% of the total sorting effect and 79.3% of the total manufacturing effect. Interpreting firm size as a proxy for firm productivity, the results of Table 8 are consistent with both the results across the EFE distribution of Table 7 and some general predic-

[35]The final row shows that 49.2% of the total 50.5% effect on sorting due to manufacturing is due to changes in employment at the top end of the EFE distribution.

tions of trade theory. Large and high-EFE manufacturing firms contribute the most to increasing sorting and they do this by increasing their share of high-WFE workers.

Although these results are broadly consistent with some predictions of trade theory, the majority of the sorting effect works through job stayers. For instance, large firms contribute 30.5% of the export sorting effect through job stayers and 7.3% through reallocation. High-EFE firms contribute 29.1% through job stayers and 11.3% through reallocation. Therefore, most of the demand shock passes through into the wages of current workers rather than towards reallocation of new, high-WFE workers.

Table 8: Decomposition of Export Sorting into Worker Flows by Industry and Firm Size

	I. Share of Change in Sorting through Exports by Industry & Firm Size						*II. Initial Employment Shares by Industry & Firm Size*					
	Manufacturing			Non-Mnfctr			Manufacturing			Non-Mnfctr		
	NC	Sml	Lrg	NC	Sml	Lrg	NC	Sml	Lrg	NC	Sml	Lrg
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Labor market entry	5.4	2.2	-5.2	28.8	6.6	10.2	4.4	3.3	6.0	10.0	2.6	7.2
Between-LLM job-to-job	*2.5*	*1.1*	*4.8*	*9.7*	*1.3*	*-2.7*	*2.3*	*1.4*	*1.8*	*5.7*	*1.6*	*2.6*
Within-LLM job-to-job	*0.9*	*-0.5*	*2.6*	*1.3*	*1.5*	*3.7*	*3.1*	*1.1*	*3.6*	*5.0*	*0.1*	*-0.1*
Job-to-job	3.4	0.6	7.3	11.0	2.7	1.0	5.4	2.5	5.4	10.7	1.7	2.5
Other to emp.	*0.5*	*-1.2*	*8.7*	*2.6*	*1.7*	*-2.4*	*1.2*	*1.0*	*1.3*	*3.4*	*1.3*	*1.8*
Unemp. to emp.	*0.6*	*-1.3*	*-1.4*	*0.4*	*0.8*	*1.3*	*0.6*	*0.5*	*0.8*	*1.2*	*0.4*	*0.7*
Nonemployment to emp.	1.1	-2.5	7.3	2.9	2.5	-1.1	1.8	1.4	2.1	4.6	1.8	2.4
Job Stayers	0.0	0.2	30.5	0.0	-3.4	-2.2	0.0	4.3	7.2	0.0	3.5	6.7
Industry total	9.9	0.5	39.9	42.8	8.4	7.9	11.7	11.6	20.6	25.3	9.6	18.9

Notes: Estimates of contributions of worker flows to export-induced LLM sorting based on the methology of Section 6.1. Panel I presents the contribution of a given worker flow as a share of the total export-induced change in sorting. Panel II presents the initial share of a given worker flow relative to total LLM employment. "NC" refers to employment in non-continuing firms. "Sml" refers to employment in small, surviving firms. "Lrg" refers to employment in large, surviving firms.

7.3.2 Effects on the Non-Manufacturing Sector

Section 7.2 shows that the most important worker flow of the non-manufacturing sector is net labor market entry. In fact, there is a relative inflow of entrants to non-manufacturing despite the fact that the demand shock targets the manufacturing sector. I turn to a discussion of the results of the sorting effect of exports on changes in non-manufacturing employment across the firm-type distribution to clarify the nature of these flows from labor market entry.

Panel I of Table 7 reports the contributions of different worker flows to export-induced sorting across the EFE distribution. Net labor market entry affects sorting through both low- and high-EFE firms. The largest contributors, however, are low EFE firms with a 32.8% contribution which comprises 71.8% of the total contribution of non-manufacturing firms through labor market entry. Although low-EFE firms comprise large share of non-manufacturing employment, their sorting contribution is roughly 50% greater than their employment share. The large contribution of low-EFE firms implies that flows of low-WFE workers to low-EFE firms contribute significantly to increased LLM sorting.

This message is confirmed when looking at the relative contribution of labor market entry by firm size in Table 8. Non-continuing firms, either exiting in the lag period or exiting in the lead period, constitute the largest share of the effect of net labor market entry–accounting for 28.8% of the total effect and 62.6% of the non-manufacturing effect. Non-continuing firms comprise 50.5% of employment by labor market entrants and exiters, but yet, produce a disportionate effect on sorting by accounting for 62.6% of the total effect. These results are, therefore, consistent with the interpretation that demand shocks in the manufacturing sector lead to large relative entry of low-WFE workers to new, low-EFE firms in the non-manufacturing sector.

Non-manufacturing sector reallocation also contributes to sorting. In contrast to manufacturing sector reallocation, low-EFE and non-continuing firms fully account for the sorting effects of non-manufacturing reallocation. This provides evidence that the composition of regional entrants to the non-manufacturing sectors shifts toward low-WFE workers.

7.4 Implications of Sorting at Labor Market Entry

An important result has been to show that export shocks to the manufacturing sector induce relative movements of entrants away from manufacturing and toward non-manufacturing jobs. These entrants tend to have low WFE's and work for low-EFE firms. On its face this is a counterintuitive result as the manufacturing industry experienced a positive shock. In order to make some sense of this result I will investigate two potential hypotheses.

First, an increase in manufacturing demand may have spillover effects into other industries. Specifically, the growth of the manufacturing sector may lead to an increase in demand for manufacturing inputs. An example of an industry supplying inputs is the business service industry. Business service firms include food, janitorial, and security services.

To investigate this hypothesis I estimate the effect of export shocks on growth in business service industries. I estimate a positive coefficient of 1.201 but it is insignificant with a p-value around 0.12. This null result is consistent with the result on aggregate employment changes in the non-manufacturing industry. Although the export coefficient for change in total non-manufacturing employment is positive at 0.55 log points, it is insignificant with a p-value of 0.22. Therefore, there does not appear to be large spillover demand effects into the non-maunfacturing industry.

A second hypothesis is that firms react to demand shocks by not only increasing employment and output, but by upgrading their technology.[36] Export markets offer the opportunity to increase the scale of operations. An increase in scale induces capital investments that require large fixed costs. Technology on the other hand is ofter viewed as complementarity to a skilled workforce. Therefore, investments may reduce the relative demand for low skill workers. Previous empirical work supports the idea that trade induces firm to upgrade their technology. Both Lileeva and Trefler (2010) and Bustos (2011) find evidence that trade liberalization leads to technological investment in Canada and Argentina, respectively.

In order to investigate this hypothesis, I utilize a data set of employment histories, the LIAB, which can be merge with an establishment-based panel survey, the Establishment History Panel (BHP). The survey provides responses to a variety of questions about the workforce composition and operations of the establishment. Importantly, it asks respondents to list the total value of all investments undertaken in the previous year.[37] Therefore, the LIAB provides an account of the evolution of firm investment over time.

I replicate the trade shock estimation strategy of equation (15) with the data from the LIAB. However, the sample size of the establishment panels is significantly smaller than the SIAB. As the survey is available only from 1990 onwards, I am unable to construct the first estimation interval from 1985 to 1991. The survey sample has expanded through time, so there are more firms in more recent years. In the end I am left with 218 and 648 establishments in the 1990-1996 and 2003 to 2009 intervals, respectively. The sample limitations constrain the regression specification such that I only include state fixed effects and cannot estimate the two-stacked-differences structure.

Despite the sample limitations, I find a significant effect of export shocks on investment in manufacturing firms but not in non-manufacturing firms. I estimate a coefficient on export exposure of 1.107 with a standard error of 0.425. The coefficient is significant at the 0.01% level with a p-value of 0.009.[38] This result is consistent with a story in which manufacturing firms upgrade their technology and reduce their demand for low-skill labor. Young entrants are then left to find jobs in less well-compensated industries such as the retail trade and service sectors. This story fits with the long-term features of the manufacturing industry. Employment in manufacturing, even

[36] This mechanism is modeling in a trade context by Sampson (2014).

[37] They also asks respondents to evaluate the technical status of their equipment. Respondents are given a choice of stating the state of their equipment as either “obsolete”, “rather obsolete”, “medium”, “rather state-of-the-art”, or “state-of-the-art”. Given the discrete nature of the responses and the fact that the majority of establishments pick “rather state-of-the-art”, this variable may be a less objective and reliable measure.

[38] I fail to replicate my results in the SIAB on employment and wages. The coefficients are positive, but insignificant. I suspect the insignificance of these results are due to the small sample sizes. There are far too few firms in each LLM to construct an accurate measure of within-LLM sorting to attempt to replicate the sorting resutls. Results of these regressions are reported in the appendix.

in Germany, declined significantly from the 1980's through the 2000's. However, manufacturing output has continued to rise. Therefore, capital increasingly plays a larger role in the production of manufacturing goods and increases in demand appear to accelerate this process.

8 Conclusion

Although labor market sorting is a significant contributor to inequality, the channels and sources of its rise remain unclear. I combine a novel worker flow decomposition method with exogenous trade shocks to understand how and why sorting is rising. My main finding is that young workers are becoming more sorted at labor market entry over time. By performing a decomposition of exogenous, export-induced worker flows, I confirm this descriptive statistic and alleviate concerns over changes in worker composition. For a given distribution of skill types, entrants are becoming more sorted in recent decades, i.e. high-wage entrants are matching with high-wage firms.

The finding of increased sorting at labor market entry has important implications for inequality. As high-wage workers are sorted into high-wage firm at earlier stages in their careers, the effects on lifetime inequality will be greater as high-wage workers earn firm premiums for longer durations. Furthermore, an increase of sorting at entry suggests that the factors that generate individuals' initial productivity, such as education and childhood environment, are important determinants of lifetime sorting and inequality.

In addition, these results highlight demand shocks as a potentially important source of rising sorting. Trade from Eastern Europe and China alone can account for 14% of the total rise in sorting in West German over the period 1985 to 2009. Given that the export-induced sorting flows are similar to the aggregate sorting flows and trade with the East accounts for small portion of international and domestic trade, increases in demand can potentially explain a large share of the total rise in West German sorting. This result is consistent with a story of rising sorting due to complementarities between firm technology and worker skill which are amplified by demand shocks.

By analyzing export-induced worker flows, we gain a better understanding of the impact of exports on sorting. I find that shocks to the manufacturing industry have large effects on labor market entry in non-manufacturing sectors. Specifically, low-wage workers tend to enter to low-wage firms. To explain this result I hypothesize that manufacturing firms increase investment to take advantage of increases in demand. As a result, low-skill workers have few employment opportunities and, therefore, enter industries that pay lower firm premiums. I find support for this hypothesis by estimating a significant effect of export shocks on investment.

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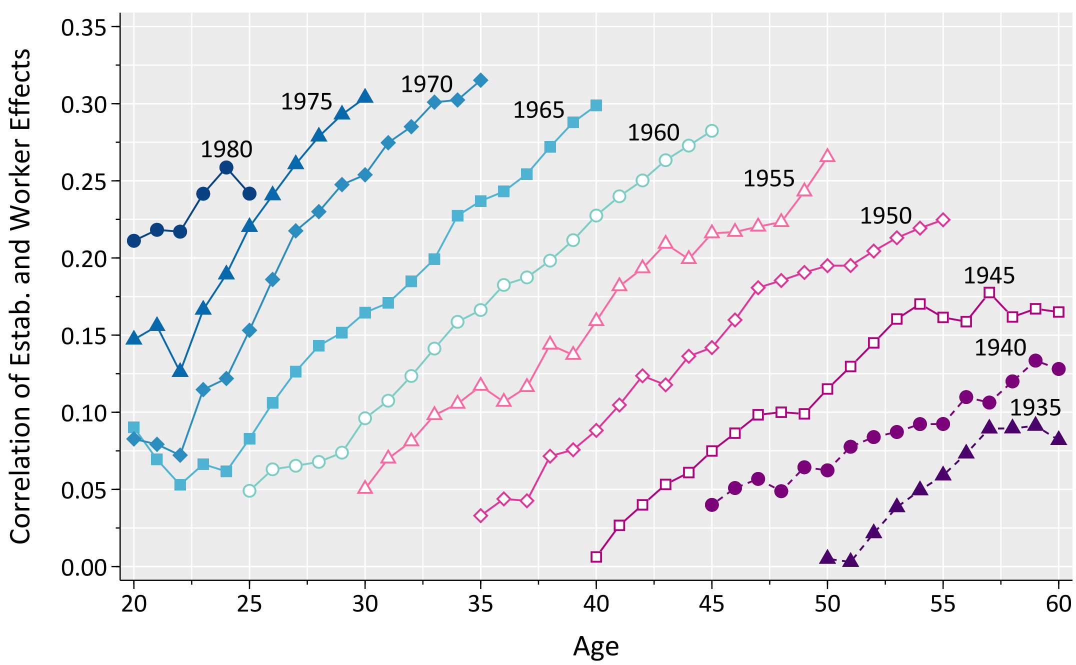
Appendices

A Descriptive Patterns of Sorting Over the Life-Cycle and Over Time

The purpose of this section is to identify potentially important factors for the rise of sorting with descriptive evidence. This evidence provides a basic understanding of how the sorting process evolves over the career and how these processes have been changing over time. To provide an organizational structure, I describe the potential factors in terms of age, year, and cohort effects.

Figure A1: Sorting Over the Life-Cycle by Year-of-Birth Cohort



Notes: YOB cohorts labeled within the plot region. Each data point represents the average value of the correlation of establishment and worker fixed effects across five YOB cohorts. For example, 1980 represents an average across all years from 1980 to 1984.

Figure A1 plots sorting of worker and firm types by year-of-birth (YOB) cohort and age. Consistent with Section 3, sorting is defined as the correlation between establishment and worker fixed effects. A notable distinction here, however, is that this measure is computed *within* YOB and age groups. Total labor market sorting is a function of both within- and between-group effect. This analysis, therefore, focuses on one component of total sorting.[39] Each data point in the figure represents an average measure of sorting across five separate YOB cohorts. The label for each line

[39] Section D suggests that within-group effects may be the more important component of the rise in sorting. The results indicate that most of the change in sorting is due to within-group changes in the joint distribution of establishment and worker effects. However, the "groups" in this section include worker flow states, firm size, and industry.

corresponds to the earliest year of a five-year group. For example, the line labeled 1935 represents average sorting for YOB cohorts 1935 through 1939 at each specified age.

Figure A1 presents two key facts. First, within a given cohort, sorting is rising with age. This fact is represented in the positive slope of each of the YOB cohort lines. Second, sorting is higher in younger cohorts. Indeed, at any given age, sorting is always higher for the younger than the older cohort.[40]

In terms of age, year, and cohort effects, there are two stylized hypotheses that can explain these facts. The first hypothesis is that age effects are positive and constant, year effects are constant, and cohort effects are increasing. The second hypothesis is that age effects are constant, year effects are increasing, and cohort effects are constant.[41] Throughout the course of this section, I argue that the first hypothesis fits the data best and, therefore, the rise is sorting is the result of increasing cohort effects.

The fact that age, year, and cohort effects cannot be jointing identified is a classic problem without a ready solution. Researchers need to make assumptions about some features of these effects in order to jointly identify them.[42] Given that the life-cycle pattern of sorting is poorly understood, I refrain from using one of these methods. In the following discussion, I provide an explanation of the two key facts of Figure A1 using patterns in the data. Although the evidence presented in this section is descriptive, it helps build intuition to understand the causal evidence presented in Section 5.

A.1 Fact 1: Why does sorting rise with age?

Before considering changes in sorting over time, first consider the growth in sorting over the life-cycle. For expositional purposes, I focus on the 1965-1969 YOB cohort. For this cohort, my sample covers 20 years of observations from age 20 to 40. In Section A.2, I turn to the question of whether sorting patterns are stable over time.

Figure A2 provides an alternative representation of the rise in sorting over the life-cycle. Each individual is classified into one of four worker fixed effect (WFE) quartiles between the ages of 20 and 40. These quartiles are computed at the worker level, therefore, at any given age there may be more individuals in a given quartile if they are more likely to be employed. Each line plots the average establishment fixed effect (EFE) for each quartile at each age.

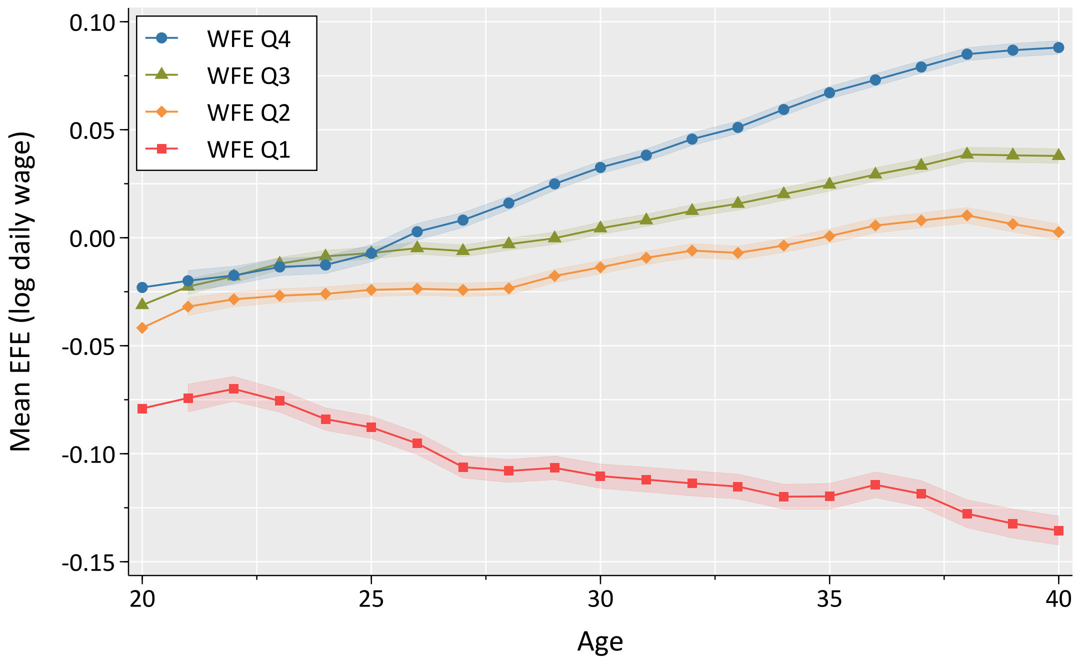
The figure shows a few key results. First, consider the early career stages from ages 20 to 25. Initially at age 20, the rank ordering of average EFE is consistent with the rank ordering of WFE

[40]The single expection is at age 20 YOB cohort 1965 is more sorted than YOB cohort 1970.

[41]A third stylized hypothesis woudl be that year and cohort effects are constant and age effects are increaseing over time–creating a steeper slope in the age profile of sorting. However, this hypothesis seems difficult to reconcile with the paterns in Figure A1.

[42]See Hall (1968), Deaton (1997), Card and Lemieux (2001), Heckman et al. (1998), and Lagakos et al. (2016).

Figure A2: Average EFE Over the Life-Cycle by WFE Quartile for YOB Cohort 1965-1969



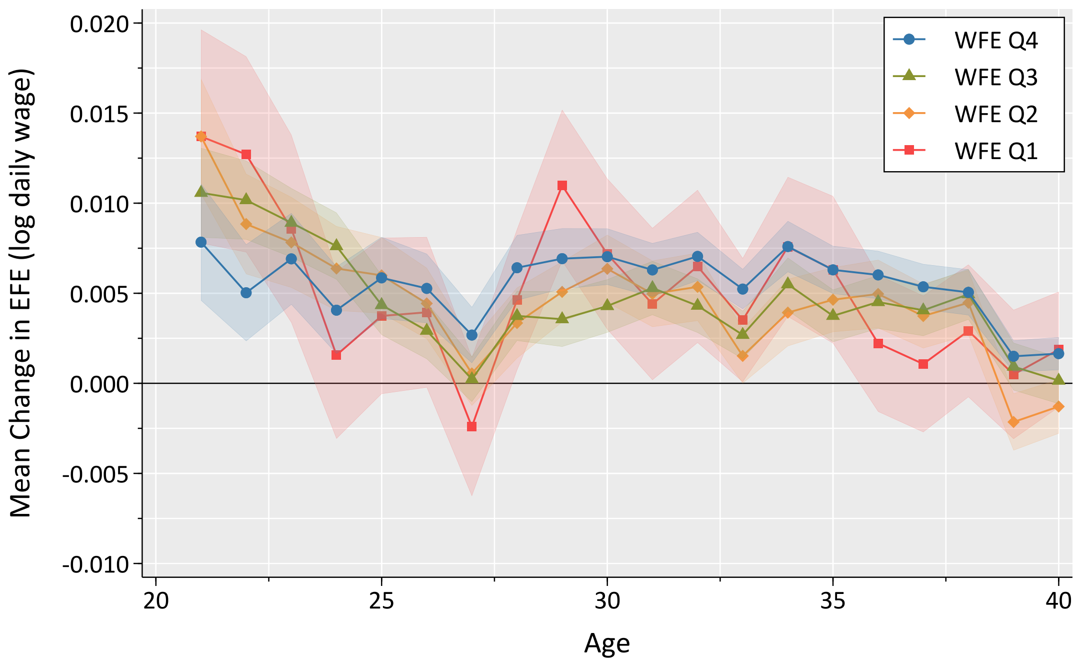
Notes: Each age t on the x-axis represents the transition between age $t-1$ and t.

quartile, with WFE Q4 earning the highest firm premium and WFE Q1 the lowest. In the next five years, the average EFE for Q2 and Q3 rises steadily, while the average EFE for Q4 rises only moderately, and the average EFE for Q4 falls slightly after an initial increase. Given that EFEs of WFE Q2 and Q3 workers rise faster than WFE Q4 workers, the effect on sorting is ambiguous. Indeed, Figure A1 shows that sorting is roughly constant during this period (initially falling and subsequently rising).

After the age of 25, however, we see a clear trend toward greater dispersion in EFEs across WFE quartiles. The average EFE of WFE Q4 rises rapidly, WFE Q2 and Q3 resume their steady march upward, and the averge EFE of WFE Q1 workers continually declines. Over the course of 20 years, the difference between the average EFE in WFE Q4 and WFE Q1 grows from about 10 log points at age 20 to 22.5 log points at age 40. This in turn leads to a sharp increase in within-cohort sorting, as shown in Figure A1. To understand life-cycle sorting, two questions become apparent. First, why does the average EFE of WFE Q1 workers fall? Second, why does the average EFE of WFE Q4 workers rise faster than WFE Q2 and Q3 workers?

To address these questions, I deconstruct the changes in EFEs over time into the effects of two types of transitions: employment-to-employment and employment-to-nonemployment. This classification helps us to understand whether the differential growth in EFEs is caused by the return to staying employed or the cost of incurring a nonemployment transition. In investigating these transitions, I report statistics on the differential probabilities and returns to each transition across workers types.

Figure A3: Change in EFE Given Stay Employed Over the Life-Cycle by WFE Quartile for YOB Cohort 1965-1969



Notes: Each age t on the x-axis represents the transition between age $t-1$ and t.

The literature typically focuses on the role of job-to-job transitions to explain sorting (e.g. Hagedorn et al. 2017, Lopes de Melo 2016). Therefore, one natural story for increasing dispersion in EFEs is that high WFE workers move to higher wage firms over time while on the job. To investigate this channel, Figure A3 plots the average change in EFE by each WFE quartile for one-year transitions. As the figure includes all employment-to-employment transitions it accounts for both changes in the EFE due to job changes and increases in an estlabishment's EFE over time.[43]

The main result of Figure A3 is that all workers tend to incur similar growth in their EFEs while employed–and this is particularly true after age 25. The shaded regions of the figure represent 95% confidence intervals for each quartile. As all the confidence intervals overlap past age 25, we are unlikely to reject the null hypothesis that the gains in EFEs while staying employed are the same across worker types. Therefore, perhaps surprisingly, differential returns to job-to-job transitions are unlikely to account for the life-cycle profile in sorting.

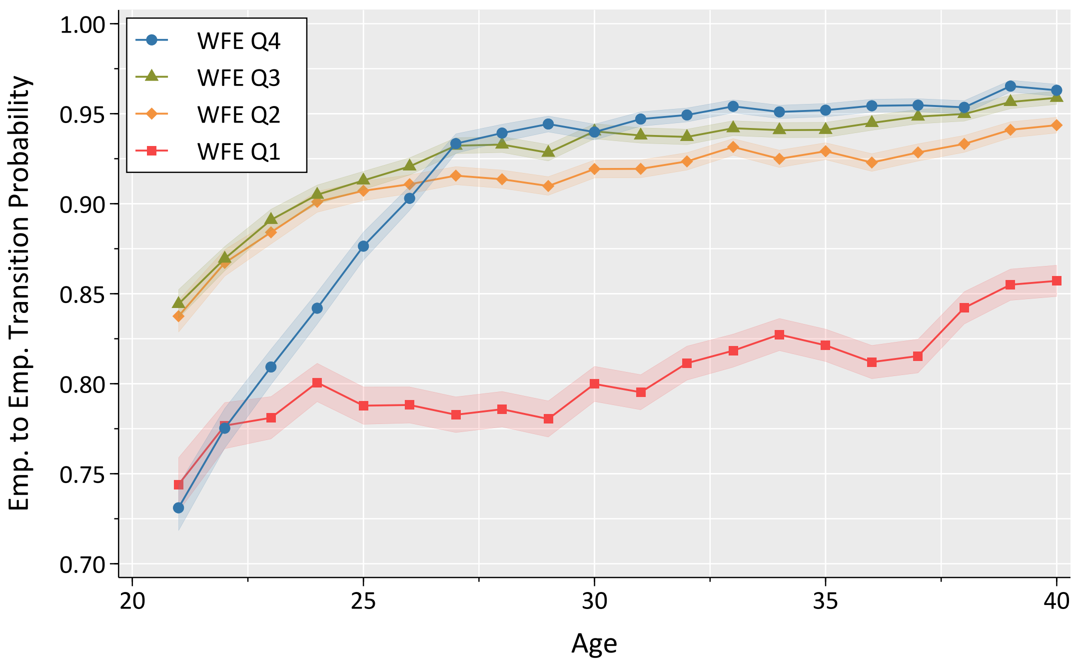
Another interesting result is that until about age 38 most workers tend to improve their EFE

[43]EFEs are computed for the same firm in multiple periods and, therefore, may grow over time. More detailed figures of the effects of changes in EFEs due to job switching and job staying can be produced upon request.

with experience. In order words, early career workers tend to slowly transition to higher paying firms. This is partly the result of the fact that workers tend to transition to higher paying firms and partly that surviving firms tend to increase their firm wage premiums.

Another possible explanation for the growth in sorting over the life-cycle is that different worker types have different probabilities of staying employed. If workers face a loss in their EFE following a nonemployment transition, then a higher incidence of these transitions will lead to slower growth in EFEs.

Figure A4: Probability to Stay Employed Over the Life-Cycle by WFE Quartile for YOB Cohort 1965-1969

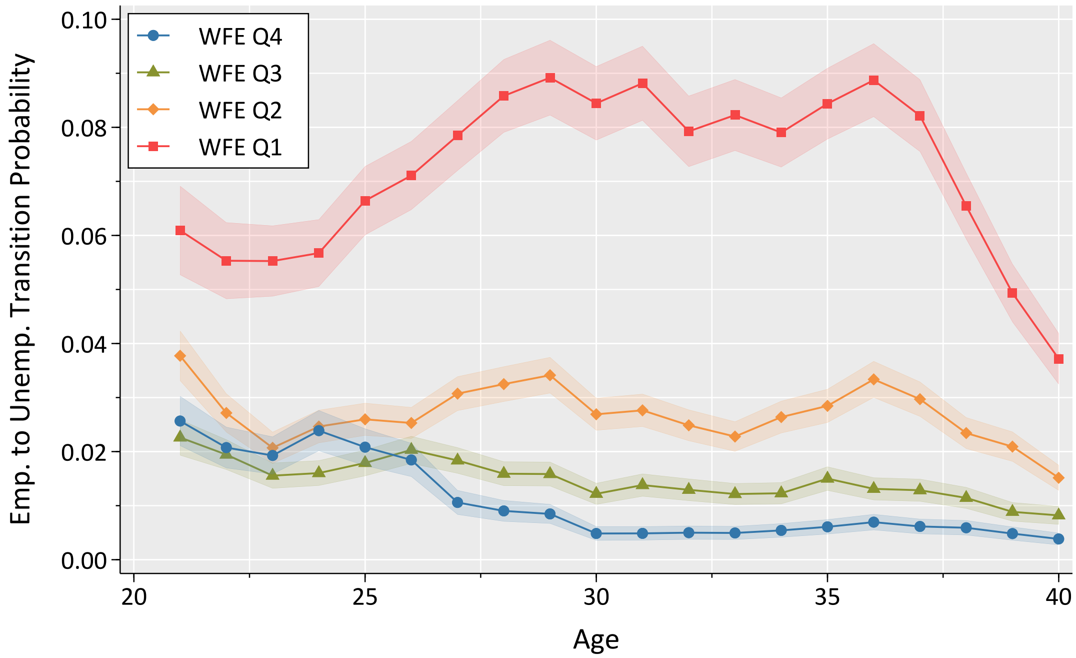


Notes: Each age t on the x-axis represents the transition between age $t-1$ and t.

Figure A4 plots the annual probability of staying employed by WFE quartile and age. A few features are of note. First, there is a steep rise in the probability of staying employed for the top WFE quartile of workers from ages 21 to 27. This feature suggests that transitions between the labor force and schooling last until the late 20s WFE Q4 workers. Also it suggests that high-wage workers are indeed high-skill workers. After the age of 28, however, WFE Q4 workers are the most likely to stay employed. Although the differences in the probability of staying employed between WFE Q3 and Q4 are quite small, the standard errors are small enough to, in many cases, produce statistically significant differences.

Another striking feature of Figure A4 is that WFE Q1 workers face a low probability of staying employed. From ages 20 to 40, WFE Q1 workers are consistently over 10% more likely to face a

Figure A5: Probability to Transition to Unemployment Over the Life-Cycle by WFE Quartile for YOB Cohort 1965-1969



Notes: Each age t on the x-axis represents the transition between age $t-1$ and t.

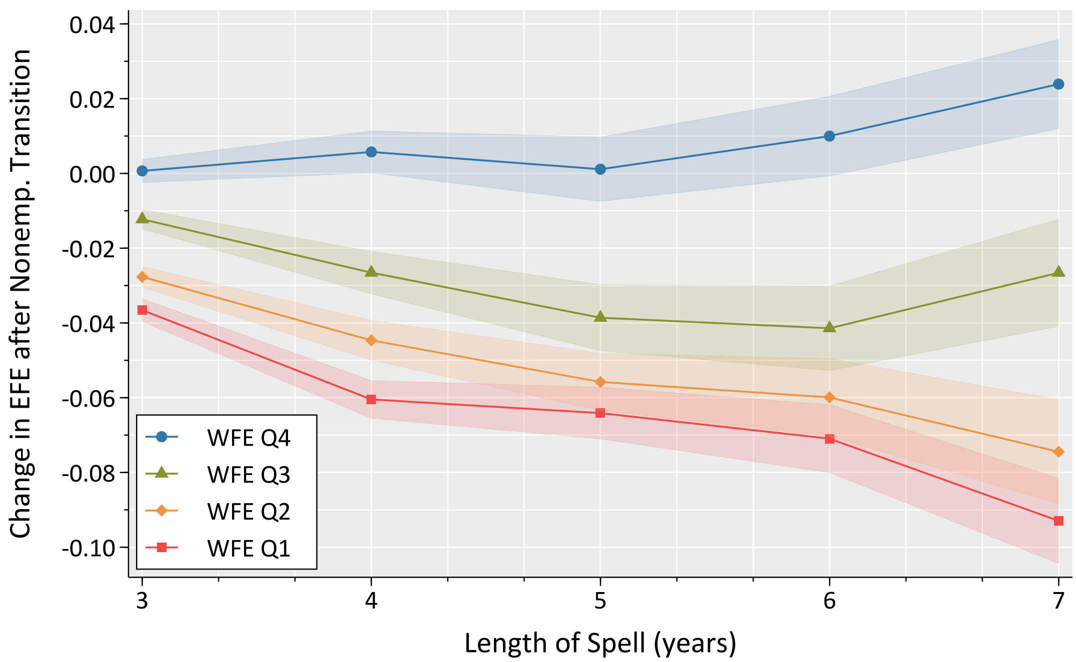
nonemployment transition. Given the stability of this disparity over the life-cycle, it is unlikely that these differences reflect differences in the probability of transitioning to schooling, as we would expect schooling transitions to be concentrated in the early career. In fact, Figure A5 shows that WFE Q1 workers face a consistently higher probability of transitioning to unemployment with an average disparity of about 6% between ages 29 and 37.

Given that workers with low WFEs are significantly more likely to face a nonemployment transition, this could account for the negative growth in the EFEs of WFE Q1 workers provided that the cost of a nonempoyment spell is significant. In fact, many search models predict that workers face a risk of falling to the bottom of the job ladder after a nonemployment transition (e.g. Burdett and Mortensen 1998, Delacroix and Shi 2006, Jarosch 2015, and Krolikowski 2017).

Figure A6 plots estimates of the cost of nonemployment transitions by comparing the initial EFE before a nonemployment spell with the re-employment EFE. The x-axis reports the spell length of an employment sequence ranging from three to seven years. Using this notation, a three-year spell represents a sequence of employment states such that the individual is employed in the first year, nonemployed in second year, and then re-employed in the third year. Hence the sequence labeled as a three-year spell represents changes in EFEs across two years.

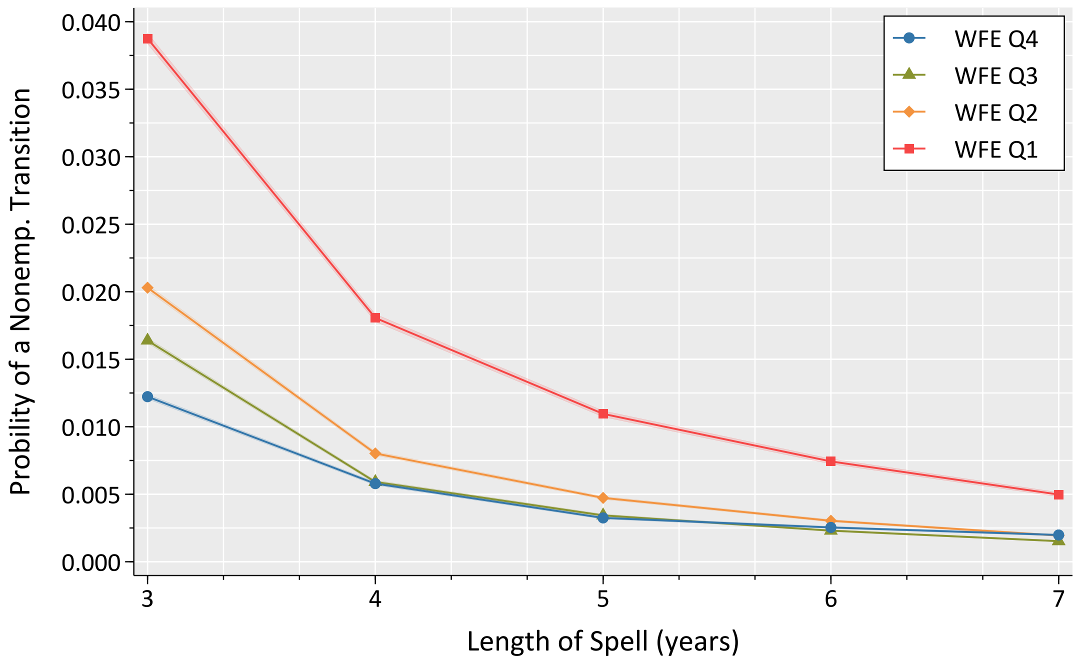
Figure A6 shows that for WFE Q1, Q2, and Q3 workers there is a significant cost of incurring

Figure A6: Cost of a Nonemployment Transition by Worker Type



Notes: A spell with a nonemployment transition includes a spell of nonemployed bookended by a year of employment. For example, a spell of length 5 denotes the sequence: E, N, N, N, E, where E denotes employment and N denotes nonemployment. Differences in wages for a spell of length t are then computed across $t-1$ years.

Figure A7: Probability of Incurring a Nonemployment Transition by Worker Type



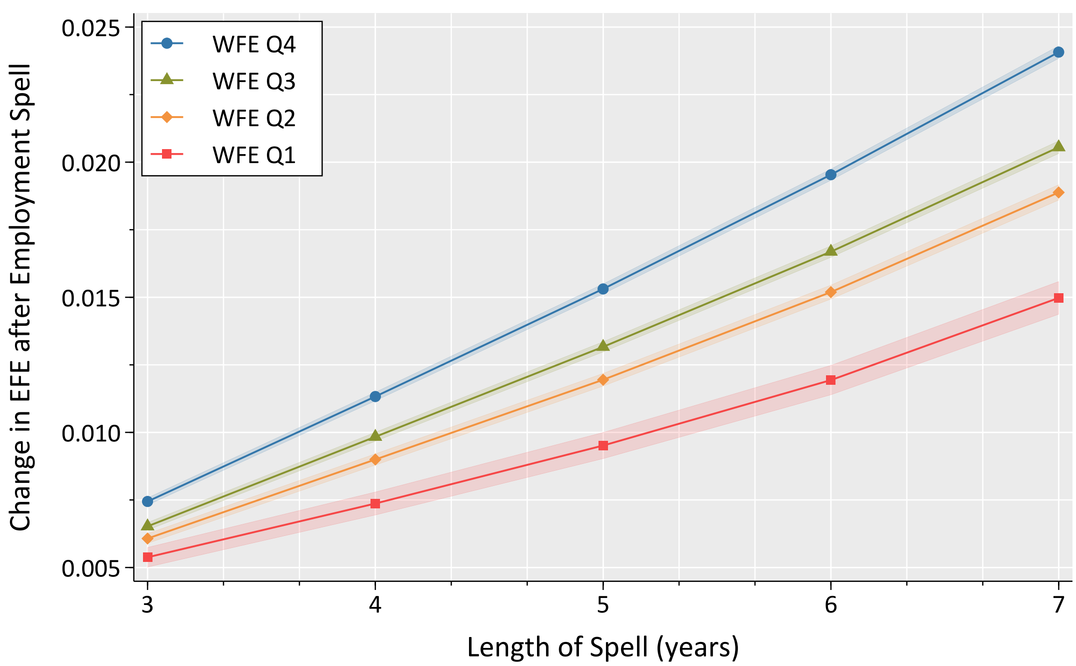
Notes: A spell with a nonemployment transition includes a spell of nonemployed bookended by a year of employment. For example, a spell of length 5 denotes the sequence: E, N, N, N, E, where E denotes employment and N denotes nonemployment.

a nonemployment spell. Furthermore, the cost of the transition grows with the duration of the spell. For instance, Q1 workers initially face an average loss in EFEs of about 4 log points. This loss grows to about an 11 log points in a seven-year spell (five years of nonemployment). On the other hand, WFE Q4 workers do not suffer losses in their EFE when transitioning through nonemployment. These differences further suggest that high-wage workers experience different types of nonemployment spells than low-wage workers. If high WFE workers are more likely to transition through school rather than unemployment, the cost of nonemployment would be expected to be smaller.

Both the high incidence and high cost of nonemployment for WFE Q1 workers suggests that the nonemployment channel is an important source of the decline in EFEs for low wage workers over the life-cycle and, hence, an important factor in the rise of life-cycle sorting. To understand the magnitude of this channel, Figure A3 shows that growth in the mean EFE for WFE Q1 workers is -5.65 log points from age 20 to 40 whereas the mean EFE for WFE Q2 workers grows 4.44 log points. Hence the gap in EFEs between WFE Q1 and Q2 grows by 10.09 log points in 20 years. Considering only nonemployment spells of five year or less (total spells of seven years or less), I use the cost of nonemployment spells (reported in Figure A6) along with the probability of incurring such a spell (reported in Figure A7) to estimate that over 20 years nonemployment spells result in a relative loss in EFEs of 4.45 log points for WFE Q1 relative to WFE Q2. This represents about 45% of the total career mean EFE growth differential of 10.09 log points, but is a lower bound since it does not included nonemployment spells longer than five consecutive years.

On the other hand, Figure A8 reports the cumulative growth in EFEs of workers who stay employed by worker type. Even while consistently employed, the dispersion in mean EFEs grows with time. Although these differences are statistically significant, they are small. For example, if I linearly extrapolate the growth in EFE dispersion out to 20 years, the difference in mean EFE growth between WFE Q1 and WFE Q2 amounts to -0.93 log points. This differential represents an estimate of difference in EFE growth if both groups were fully employed over the ages 20 to 40 and, hence, is an upper bound of the effect of on-the-job EFE growth. Therefore, nonemployment transitions appear to be the main determinant of increased sorting at the low end of the WFE distribution.

Figure A8: Return to Staying Employed by Worker Type

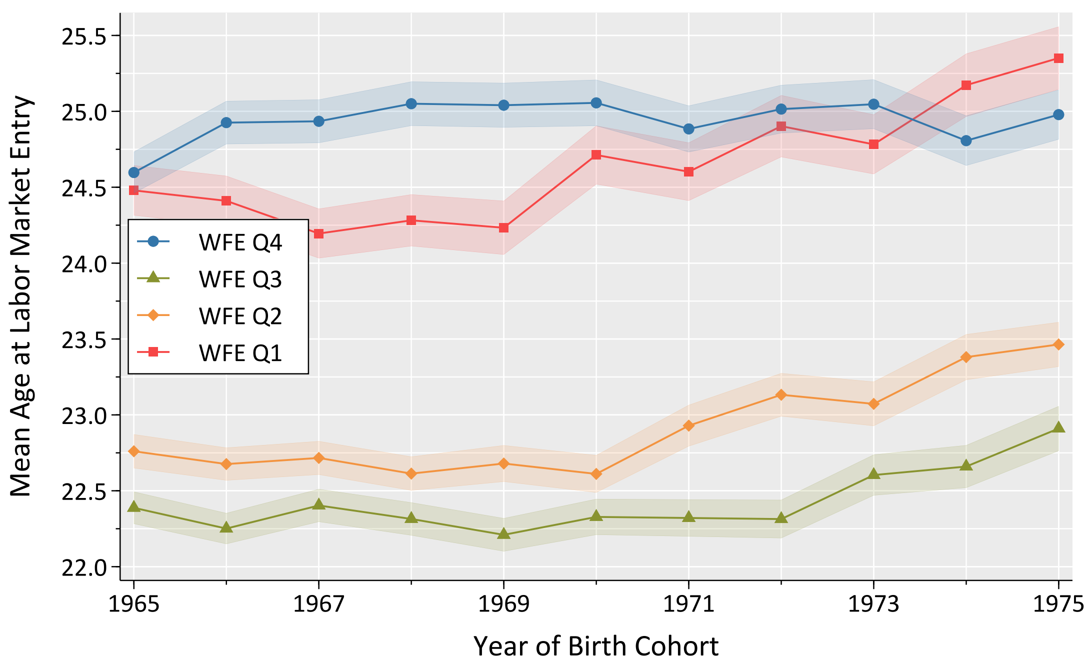


Notes: Differences in wages for a spell of length t are computed across $t-1$ years.

Another factor in rising sorting is the steep rise in EFEs for high-wage workers throughout their careers. Figure A4 shows that WFE Q4 workers are relatively less attached to the labor force than WFE Q3 or Q2 workers until the age of 27. Due to their high lifetime earnings potential, this instability is likely the result of transitions in and out of schooling. Therefore, the initial low level and low growth of EFEs in Figure A2 likely results from the fact that many of these workers are taking temporary jobs with firms that due not reflect their full earnings potential. The faster growth in the average EFE between ages 25 and 27 likely reflects labor market entry into more permanent career jobs.

Figure A9 provides some evidence for the claim that high WFE workers are more likely to permanently enter the labor market at older ages. The figure plots the average age at which individuals begin their first three consecutive years of full-time employment between the ages 20 to 32.[44] Note that WFE Q4 workers consistently enter one to two years later than WFE Q3 and Q2 workers. WFE Q1 workers also enter later, but this likely reflects the fact that WFE Q1 workers are not firmly attached to the labor force at any point. Therefore, a more appropriate definition of labor market entry for Q1 workers may be the first year of full-time employment.

Figure A9: Average age of "permanent" labor market entry by WFE quartile and YOB cohort



Notes: "Permanent" labor market entry denotes the first consecutive three-year employment spell of an individual between the ages of 20 and 32.

Given the differential entry patterns between WFE Q4 workers and WFE Q3 workers, selection may play an important role in explaining different life-cycle trends in the early career years between these groups. In any case, most of the differential growth rate in average EFE comes after the age of 27. Thus I focus on differential EFE growth from age 27 to 40 for my analysis of the top end of the worker skill distribution.

[44] I restrict the age of entry between ages 20 and 32 to make the statistic comparable across YOB cohorts. Since my sample ends in 2009, I observe older cohorts for more years and at older ages. Hence, the sample contains more years for these cohorts to potentially enter the labor market. Late entrants can push the average age of entry up. To make the statistic comparable I condition on an age range over which all cohorts are equally represented in the sample.

There appear to be two reasons for the divergence in EFE growth. Figure A4 shows that WFE Q4 workers are more slightly more likely to stay employed at all ages from 27 to 40 with an average differential between WFE Q3 (WFE Q2) workers of 0.9% (2.6%) during these years. Furthermore, Figure A5 shows that most of this difference is due to to fact that Q4 workers are likely to experience a transition to unemployment and, hence, less likely to experience a costly nonemployment transition. The average differential in the probability of incurring an unemployment transition between WFE Q4 and WFE Q3 (WFE Q2) workers is 0.7% (2.1%).

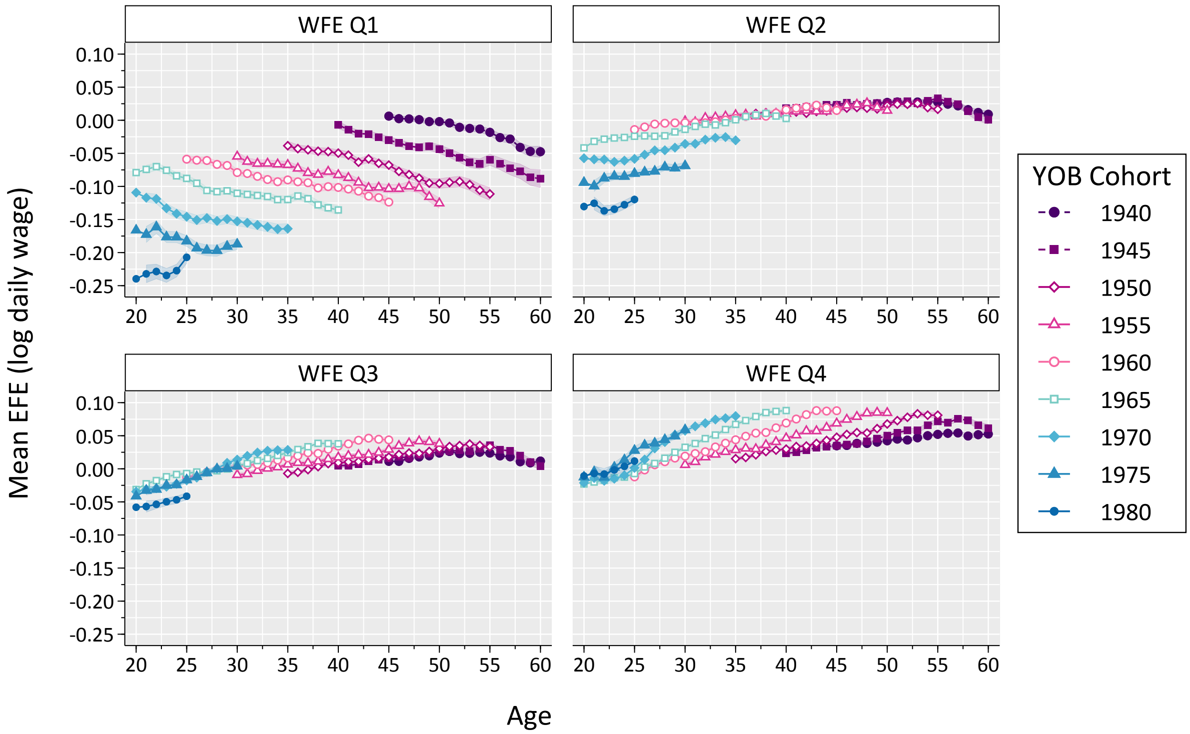
Another cause of the higher growth in EFEs for WFE Q4 workers is that they experience slightly higher growth in EFEs while staying employed. In any given year, the difference in earnings growth is insignificant (Figure A3), but over time significant differences materialize (Figure A8). To put the magnitude of the two channels in perspective. Figure A3 implies that the growth in EFEs of WFE Q4 workers was greater than WFE Q3 workers by 3.59 log points from age 27 to 40. The estimate of the differential cost of nonemployment transitions between WFE Q4 and Q3 workers using only nonemployment spells of five years or less for this length period is 0.70 log points (a lower bound). The estimate of the differential return to staying employed between WFE Q4 and Q3 for 13 years is 1.16 log points (an upper bound as the estimate assumes full employment for each group over the period.) Therefore, the two channels are of roughly equal magnitude, suggesting that the movements up the job ladder are more consequential for sorting at the upper end of the worker skill distribution.

In conclusion, an important driver of the life-cycle growth in within-cohort sorting is the differential incidence of nonemployment transitions by different worker types. The lowest WFE quartile workers have a substantially larger chance of incurring a costly nonemployment spell which disrupts their ascent up the job ladder. On the other hand, WFE Q4 workers both have slightly a lower chance of incurring an unemployment spell than WFE Q3 workers and a slightly higher return to staying employed which accumulate over a career to produce dispersion in the average EFE at the top of the WFE distribution.

A.2 Fact 2: Why is sorting rising over time?

I now turn to an investigation of the changes in sorting patterns over time. Figure A10 replicates the same information as Figure A2 across different YOB cohorts. For each cohort, the y-axis records the average EFE and the x-axis records age. The fact that EFEs of WFE Q1 workers shift downward over time and EFEs of WFE Q4 workers shift up over time indicates that sorting is increasing over time. In fact, for WFE Q1 workers at age 40 their average EFE declines by about 12.5 log points from YOB cohort 1945 to YOB cohort 1985. On the other hand, for WFE Q4 workers at age 40 their average EFE increases about 6 log points from the 1945 to the 1965 YOB cohort. Thus the total differential between WFE Q1 and Q4 workers widens by about 18.5 log points in 20 years.

Figure A10: Average EFE Over the Life-Cycle by WFE Quartile and Year-of-Birth Cohort

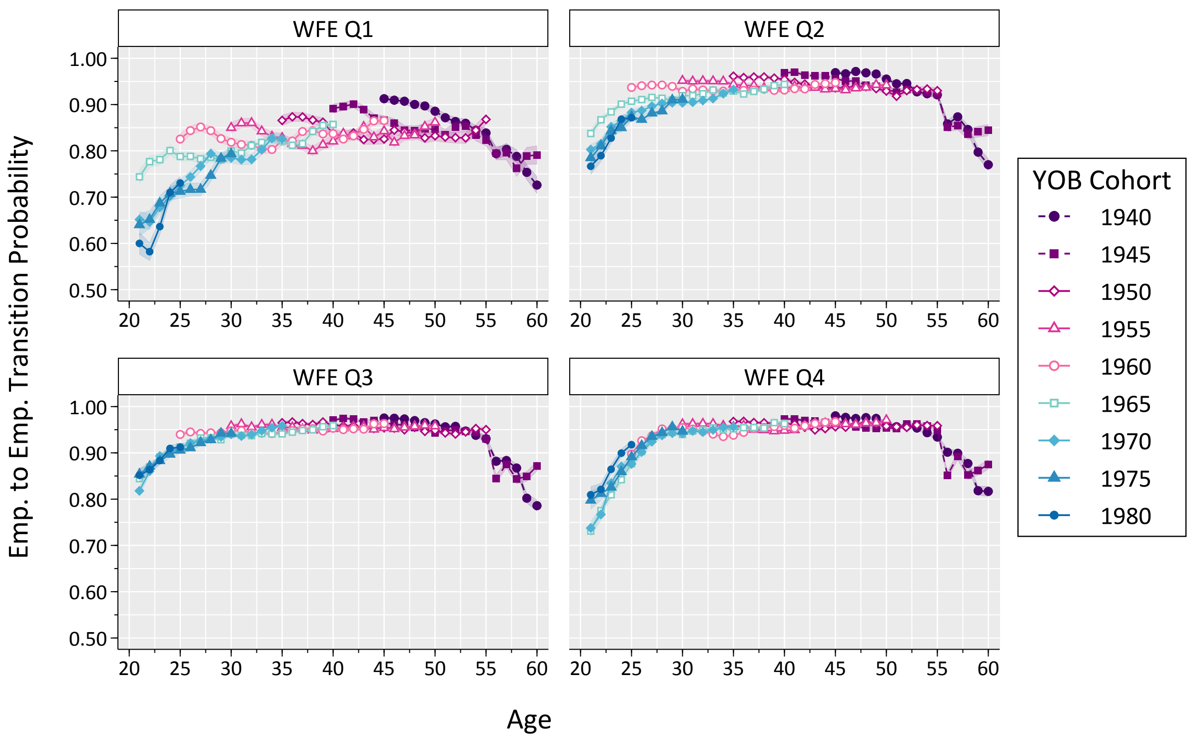


Notes:

Three broad potential mechanisms could be producing this dispersion over time. First, there could be a change in the relative probability of staying employed across worker types. Second, there could be a change in the relative return to staying employed or the relative cost of nonemployment spells across worker types. And finally, there may be a trend towards greater dispersion in the initial average EFE at labor market entry across worker types. Below I argue that the descriptive statistics support the final hypothesis, i.e. growing dispersion in initial EFEs explains most of the rise in sorting over time. Furthermore, I argue that growing dispersion in EFEs at labor market entry is consistent with an increasing cohort effect.

I discuss each hypothesis sequentially. Figure A11 shows that probability of staying employed, and hence the probability of transitioning to nonemployment, is roughly stable over time. This conclusion is clear for WFE Q3 and Q4 workers where, despite the fact that the standard errors are very small, in almost all cases with multiple observations at the same age across YOB cohorts, the confidence intervals overlap significantly. The picture is similar for WFE Q1 and Q2 with one exception. It appears that during the period from 1989 through 1993 there was a significant reduction in the probability of staying employed for workers of all ages in WFE Q1. This may suggest that German reunification put pressure on the lower end of the worker skill distribution as the supply of low-skill workers increased due to migration from East Germany and Eastern Europe. Therefore, the fall in employment security for low-wage workers represents one aspect of the rise in sorting, but only for a specific period. This would be captured as a year effect in the age/year/cohort effect framework since the effect is present for all age groups.

Figure A11: Probability Stay Employed Over the Life-Cycle by WFE Quartile for YOB Cohort

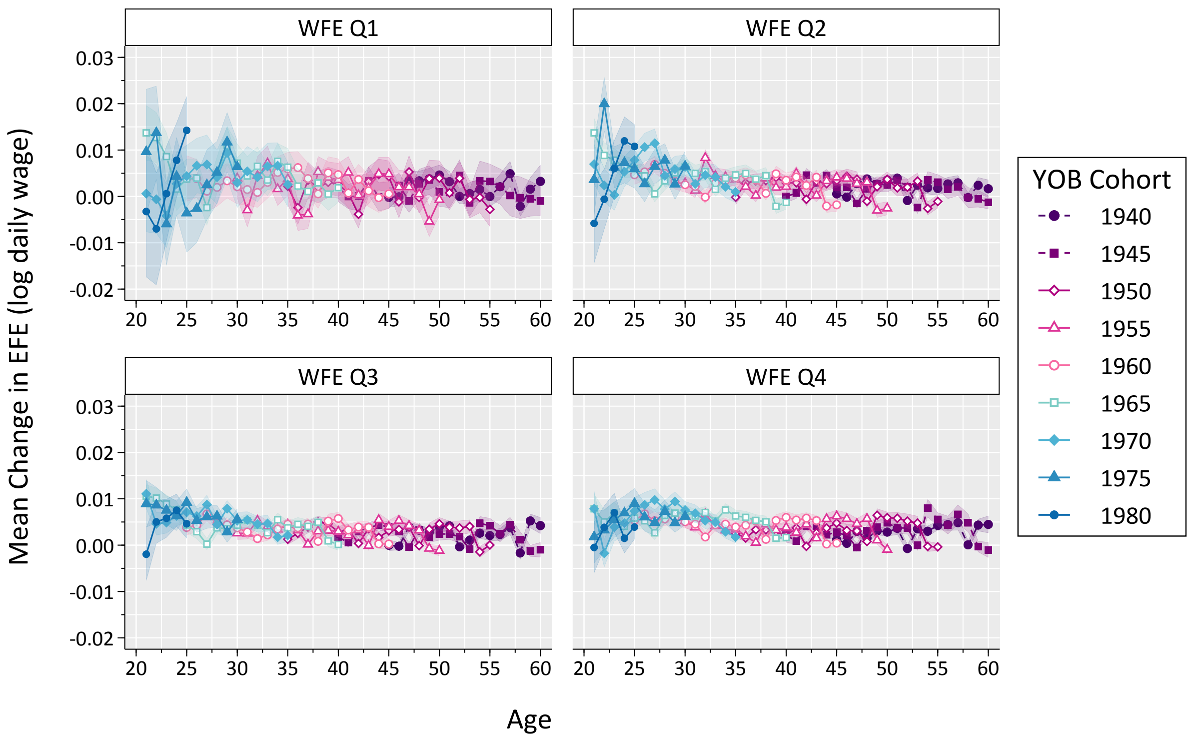


Notes:

Figure A12 shows that the return to staying employed has been roughly constant over time. As evidence for this conclusion, notice how for each WFE quartile the lines demarcating the return to staying employed lie roughly on top of each other across cohorts with the confidence intervals generally overlapping. This suggests that the return to job-to-job transitions and staying employed in a surviving firm remain roughly constant over time. Although not pictured, the cost of a nonemployment transition also remains roughly constant over time. Therefore, Figures A11 and A10 show that the life-cycle sorting patterns, in terms of the incidence and return to employment and nonemployment transitions, appear to be relatively stable over time.

On the other hand, the dispersion in the average EFE at labor market entry appears to be increasingly substantially. Figure A13 plots the average EFE at labor market entry for each WFE quartile by YOB cohort. Since this statistic relies on the ability to observe workers' employment

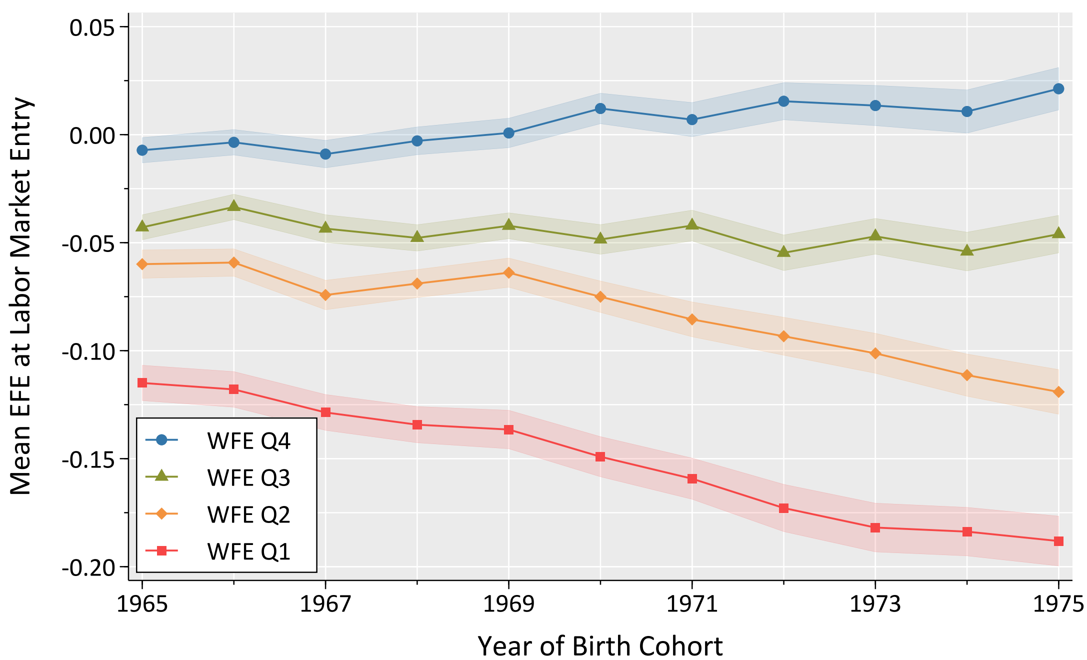
Figure A12: Change in EFE Given Stayed Employed Over the Life-Cycle by WFE Quartile and YOB Cohort



Notes:

histories between ages 20 and 32, the statistic can only be computed for a limited number of YOB cohorts. Despite short interval of observation, there is strong evidence of increasing dispersion in the average EFE at labor market entry. For instance, the differential between average EFEs at labor market entry for WFE Q4 versus WFE Q1 workers widens from 10.8 log points for YOB cohort 1965 to 20.9 log points for YOB cohort 1975. Therefore, the gap in average EFE at labor market entry grows 10.2 log points in just ten years. Figure A10 shows an increase in the dispersion of average EFEs between WFE Q4 and Q1 of about 18.5 log points in the 20 years from YOB cohort 1965 to 1985. A linear extrapolation of the change in average EFE at entry results in a 20.4 log point dispersion–accounting for the full effect.[45]

Figure A13: Average EFE by WFE quartile and YOB Cohort



Notes:

The probability of staying employed, the return to staying employed, and the cost of incurring a nonemployment transition are all approximately constant over time. Given that these factors fully characterize career growth in EFEs, the life-cycle pattern of sorting must also be approximately constant over time. Therefore, growth in sorting is not likely to be the result of age or year effects–factors which vary over the life-cycle. On the other hand, the data clearly shows growing dispersion in the initial EFE at labor market entry across WFE types. Thus the growth in sorting can be

[45] With an important caveat being that the calculations of the total change and effect of labor market entry come from different time periods.

characterized as a cohort effect, where we see a constant life-cycle profile that is steadily shifting up over time.

B Robustness of the Effect of Export Exposure on Sorting

Table A1 presents the complete results of the estimation of the effect of trade exposure shocks on local labor market sorting (equation 15). Column (1) controls for broad geographic trends with West Germany divided into 74 regions. Columns (2), the main specification, controls for more narrow geographic trends with West Germany divided into 214 regions. The first two rows report the coefficients of the endogenous variables (changes in import and export exposure) while the remaining rows present the coefficients of control variables. The control variables hold constant the initial economic conditions of local labor markets. These variables are meant to control for characteristics that may affect future changes in wage, employment, or sorting through domestic supply. The specification draws heavily from Dauth et al. (2014).

In turn I briefly discuss each control variable. The first control variable is the initial size of the local labor market in terms of employment. If there are different skill distributions on the worker side or productivity distributions on the firm side in small labor markets, then labor market size has the potential to affect sorting and possible the change in sorting over time. Labor market size appears to have a negative effect on the future growth of sorting, but this coefficient is statistically insignificant from zero at the 10% level in the main specification. The second control variable is the initial strength of sorting with a local labor market. Given that my sorting measure is a correlation and, hence, bounded by definition, changes in sorting may be non-linear. For instance, if a region starts with a high level a sorting, it may be expected to experience less growth in sorting in the future. In fact, my results confirm this pattern with a strong negative coefficient on initial sorting.

Next I control for two measures that are relevant to outsourcing: the share of employment in business service industries and the share of business service occupations in business service industries. The second variable is a measure of outsourcing used in Goldschmidt and Schmieder (2017). Business service occupations such as logistics, cleaning, food, and security services are vulnerable to outsourcing arrangements such that a firm subcontracts these services to a business service firm. These employees often perform the same duties in the same location, but are employed by a different employer. Goldschmidt and Schmieder (2017) document that outsourced workers face a decline their wages and establishment fixed effect and, as a result, the rise in outsourcing can explain about 8% of the rise in sorting. Although, the share of employment in business service industries has an insignificant effect, the most direct measure of outsourcing–the share of business service occupations in business service firms–has a positive and significant effect on sorting. This

Table A1: All Coefficients for Main Specification of Equation (15)

	IV: LMR1 (1)	IV: LMR2 (2)
Change in export exposure	0.0105***	0.0080***
	(0.0026)	*(0.0025)*
Change in import exposure	-0.0039	-0.0014
	(0.0040)	*(0.0050)*
Initial local labor market employment	-5.75E-07**	-2.50E-07
	(2.67E-07)	*(3.89E-07)*
Initial local labor market sorting	-0.5506***	-0.6185***
	(0.0474)	*(0.0670)*
Initial share of employment in business service industries	-0.0005	-0.0005
	(0.0036)	*(0.0044)*
Initial share of business service occupations in business service industries	0.0016**	0.0018*
	(0.0008)	*(0.0009)*
Initial share of employment in non-auto manufacturing	-0.0004	-0.0001
	(0.0005)	*(0.0008)*
Initial share of employment in auto manufacturing	-0.0002	-0.0005
	(0.0007)	*(0.0008)*
Initial share of employment with a university degree	0.0059***	0.0054***
	(0.0017)	*(0.0019)*
Initial foreign-born share of employment	0.0018	-0.0002
	(0.0013)	*(0.0027)*
Initial female share of employment	0.0015***	0.0017***
	(0.0004)	*(0.0005)*
# geo fixed effects	74	214
Adj R2	0.371	0.445
N (county-periods)	650	650

Notes: All 2SLS regressions are weighted by the initial size of the regional labor force. Standard errors are clustered at the LMR2 level. Standard errors in parentheses. Main specification is column (2).

result suggests that over this time period, regions with high initial levels of outsourcing were more likely to see an increase in their rate of outsourcing and, hence, increase sorting.

Next I control for measures of manufacturing concentration. As noted by Autor et al. (2013), it is important to control for the initial concentration of manufacturing employment so that comparisons of the effect of trade are made *within* the manufacturing sector. Since manufacturing employment is in long-term decline, it is important not to conflate the factors associated with the decline of manufacturing with changes in sorting patters. Given the prominence of the auto manufacturing sector in Germany, following Dauth et al. (2014) I break manufacturing employment into two components: non-auto and auto manufacturing. This helps to specifically address the concern that the results are driven by differential exposure to auto manufacturing trends. There are clear manufacturing trends in terms of employment and wages (employment is declining, wages are rising), but the prediction for sorting is less obvious. In general, manufacturing workers tend to be middle- to high-skilled and manufacturing firms tend to pay high firm premiums. Therefore, a reduction in manufacturing employment could result in less sorting as employment at the top end of the joint distribution is reduced. On the other hand, if the reduction in manufacturing employment is the result of improvements in technology that are complementary with skill, then sorting within the manufacturing industry may be increasing over time. The net result of these effects in an empirical question. As both manufacturing coefficients are insignificant, the results of Table A1 suggest that there is no trend in manufacturing sorting over time.

The final three control are standard and important measures of the composition of labor supply: education, nationality, and gender. The composition of labor supply can interact with firm types in complex ways to affect sorting. The results point to significant positive effects of the share of employment with a college degree and female. The interpretation of these results is that local labor markets with initially high level of college educated and female employment are more likely to see future increases in sorting.

Table A2 presents the same results as Table 4 except for females only. Over the period 1985 to 2009 sorting rose less dramatically for women compared to men. Table 1 shows that the total change in the correlation of worker and establishment fixed effects was 0.095 for women versus 0.231 for men. Given that sorting rose less for women, we may expect export exposure to have a weaker effect on female sorting. The main specification (reported in Column (6)) presents suggestive evidence in favor this view as the coefficient on export exposure is 0.0066 for women compared with 0.0080 for men. However, I cannot rejected the null hypothesis that these coefficients are the same. This result suggests that trade with Eastern Europe and China can account for a greater share of the rise in sorting for women than for men.

Table A3 presents the results of various robustness checks for the main results of the effect of trade exposure on local labor market sorting presented in Table 4. Columns (1) and (2) present the

Table A2: 2SLS Results of Sorting on Trade Shocks for Females

	Region fixed effect					
	OLS: None (1)	IV: None (2)	IV: State (3)	IV: LMR1 (4)	IV: LMR2 (5)	IV: LMR2 (6)
Export exposure	0.0067**	0.0073*	0.0046	0.0071**	0.0063**	0.0066**
	(0.0032)	*(0.0044)*	*(0.0039)*	*(0.0032)*	*(0.0032)*	*(0.0026)*
Import exposure	0.0017	0.0014	0.0034	0.0037	0.0034	-0.0007
	(0.0030)	*(0.0041)*	*(0.0042)*	*(0.0037)*	*(0.0044)*	*(0.0037)*
Initial sorting						-0.9006***
						(0.0037)
Labor market controls	N	N	Y	Y	Y	Y
# geo fixed effects	0	0	11	74	214	214
Adj R^2	0.033	0.027	0.030	0.064	0.089	0.409
N (county-periods)	650	650	650	650	650	650

Notes: All 2SLS regressions are weighted by the initial size of the regional labor force. Standard errors are clustered at the LMR2 level. Labor market controls include: % employment in manufacturing, % high skilled, % foreign born, % female, and % routine occupation.

results for each interval separately. With only one observation per local labor market, however, I am constrained to use broad geographic regions (LMR1) for geographic fixed effects as some of the more narrow regions (LMR1) consist of only one local labor market or county (the German term is *kreis*). Therefore, the coefficients of columns (1) and (2) should be compared with column (1) of A1 (coefficient on export exposure of 0.0105) which uses fixed effects at the comparable geographic level. The results show that the coefficient on export exposure is significant in both intervals. There is suggestive evidence that the effect is stronger in the first interval, but I cannot reject the null hypothesis that the coefficients are equal.

Column (3) presents the results of an important robustness check related to limited mobility bias. Table 3 along with previous results from Dauth et al. (2014) show that export exposure increases employment in local labor markets that experience export exposure shocks–particularly increases in manufacturing employment. As discussed in Section 3 limited mobility bias result in a downward bias in the correlation of worker and establishment fixed effect which depends on the number of job switchers per firm. As the number of job switchers increases the bias attenuates and, hence, the correlation increases. Hence, a concern for my estimation results is that the increased employment induced by export exposure leads to a greater number of job switchers per firm and hence an increase in the correlation caused by a reduction in the econometric bias rather than due

Table A3: Robustness of the Effect of Export Exposure on Local Labor Market Sorting

	Specification:					
	First Interval ‘88–‘99 (1)	Second Interval ‘93–‘06 (2)	Control for Job Flows (3)	Constant WFE (4)	Net Exposure Total (5)	Net Exposure EE vs.CH (6)
Export exposure	0.0246**	0.0161***	0.0086***	0.0066***	-	-
	(0.0118)	*(0.0054)*	*(0.0025)*	*(0.0020)*		
Import exposure	-0.0183**	-0.0050	-0.0016	-0.0012	-	-
	(0.0084)	*(0.0038)*	*(0.0050)*	*(0.0043)*		
Net trade exposure	-	-	-	-	0.0047	
					(0.0037)	
Net trade exposure Eastern Europe	-	-	-	-	-	0.0090**
						(0.0041)
Net trade exposure China	-	-	-	-	-	*0.0024*
						(0.0059)
Change in job flows per firm	-	-	-0.00011	-	-	-
			(0.00018)			
Labor market controls	Y	Y	Y	Y	Y	Y
# geo fixed effects	74	74	214	214	214	214
Adj R^2	0.266	0.346	0.443	0.436	0.440	0.446
N (county-periods)	325	325	650	650	650	650

Notes: All 2SLS regressions are weighted by the initial size of the regional labor force. Standard errors are clustered at the LMR2 level. Standard errors in parentheses. Result are with respect to men only.

to economic conditions.

Fortunately, the IAB grants access to job flows at the firm level based on the full universe of employment histories. This allows for an accurate count of the number of gross job changes per firm in each interval. To test the plausibility of this hypothesis I use the same research design in equation (15) except I insert the average number of gross job flows per firm as the dependent variable. The results show a significant coefficient on both export and import exposure at 5.340 (1.275) for export exposure and -2.236 (1.0116). Therefore, the concern that limited mobility bias may be driving the results is plausible.

In order to address this concern, I directly control for the change in job flows per firm in the regression of sorting on trade exposure based on equation (15). The result of this regression of presented in column (3) of Table A3. The coefficients on both export and import exposure essentially remain the same. Furthermore, the coefficient on the change in job flows per firm is statistically insignificant. The interpretation of this result is that local labor markets that saw a greater rise in job flows did not experience a rise in the correlation of worker and establishment fixed effects. This suggests that either the changes in average job flows per firm are too small to make a difference in terms of limited mobility bias or that the scope of limited mobility bias is small with these fixed effects. Given that the fixed effects are merged from Card et al. (2013) and based on the full universe, it is plausible that limited mobility bias is attenuated due to the large number of movers per firm that the full universe offers.

Column (4) address the question of whether the results are driven by changes in worker fixed effects across estimation intervals. In this specification, I create an alternative definition of the worker fixed effect. First, I de-mean all worker fixed effects within a given estimation interval. Next, for each worker I take the average worker fixed effect across all observation so that the worker fixed effect is constant over the life-cycle. I then use this alternative, constant worker fixed effect to define sorting in each local labor market. The results suggest that the coefficient of export exposure is slightly diminished with this alternative definition of worker fixed effects, suggesting that the changes in worker fixed effects across intervals are responsible for some of the total effect. However, I cannot reject the null hypothesis that the export coefficient is the same with the alternative definitions of worker fixed effects.

Columns (5) and (6) seek to understand the differential effects of trade exposure between Eastern Europe and China. Given that import exposure from Eastern Europe is highly correlated with import exposure from China (and also for export exposure), I cannot include components for both import and export exposure from both Eastern Europe and China in the same regression. Therefore, I use a measure of net exposure which is simply export exposure minus import exposure for Eastern Europe and China separately. Column (5) reports the results for net exposure including both Eastern Europe and China as a reference point. Column (6) presents the coefficients in a regression where both export to Eastern European and Chinese trade are included simultaneously. We can see that exposure from Eastern Europe has a stronger effect than exposure from China with a statistically significant coefficient of 0.0090 for Eastern Europe versus an insignificant 0.0024 for China. This result is consistent which evidence from Dauth et al. (2014) which shows that trade exposure from Eastern Europe has a stronger effect on employment and wages in Germany than trade exposure from China.

C A Model of Sorting within the AKM Framework

C.1 Model Setup

Suppose there is continuum of heterogeneous worker types x and firm types y where $x, y \in (0, 1)$. The output when a worker of type x and a firm of type y are matched is equal to $f(x, y) = xy$. Therefore, firm and worker types are complements as the production function is supermodular, i.e. $\partial^2 f(x,y) / \partial x \partial y > 0$. Labor is supplied inelastically with a total supply of m_x for each worker type.

Search frictions prevent firm and workers from instantaneously matching. A worker of type x receives a job offer from a firm of type y at a rate of λr_{xy} where λ represents a search friction and r_{xy} represents recruitment effort of firm type y for worker type x. Therefore, firms can choose to put more effort into finding workers of a particular type. Let $R_x = \sum_y r_{yx}$ denote the total amount of recruiting for workers of type x.

I assume a convex cost of recruiting and allow recruitment cost to be a function of both firm and worker type. Recruitment costs are given by $r_{xy}^2 c(x, y)$, where $c(x, y)$ represents a cost function. This cost function captures, in a reduced form fashion, the potential for differential recruitment costs by firm and worker type. For instance, this allows for the possibility that prestigious firms are more easily able to recruit highly productive workers. Two potential sources of lower recruitment costs for high-type firms seeking high-type workers are referral networks and preferences for amenities. If high-type firms initially hire high-type workers then it will be easier to locate other high-type workers if they share common social networks. If high-type workers have a greater preference for working at high-type firms due to, say, prestige or non-wage amenities then the reduced cost of recruitment can result from increased search effect on behalf of workers.

Once a worker and firm meet, they determine a wage to be paid to the worker, $w(x, y)$. For simplicity, I assume all workers come from unemployment and abstract from on-the-job search. Firms and workers engage in bargaining resulting in a wage setting rule of $w(x, y) = \beta xy$.[46]

[46] This is equal to Nash bargaining where the outside option of each party is equal to zero. In a world without capacity constraints in terms of employment the cost of a vacancy will be zero, so this is reasonable on the firm side. On the worker side, this is equivalent to assuming that the worker prefers work at any wage over unemployment. The presence of a minimum wage or scarring effects from unemployment help to make this assumption more plausible.

Jobs are destroyed at an exogenous rate δ. This simple wage equation maps into AKM as it is log separable in firm and worker wage components. Furthermore, the wage components map to productivity types.

Profit in period t is:

$$\pi_y^t = \sum_x \left[u_x^{t-1}\lambda r_{xy}^t + e_{xy}^{t-1}(1-\delta)\right] xy(1-\beta) - c(x,y)\left(r_{xy}^t\right)^2 \tag{18}$$

where u_x^{t-1} is the stock of unemployed of type x in period $t-1$ and e_{xy}^{t-1} is the number of workers of type x that firm y hired in period $t-1$. The costs of recruitment are convex in r_{xy} which ensures a unique solution.

C.2 Optimal Employment

The steady state aggregate flows out of unemployment must equal aggregate flows into unemployment:

$$\begin{aligned} \sum_y \lambda r_{xy} u_x &= \delta(m_x - u_x) \\ \Leftrightarrow \lambda R_x u_x &= \delta(m_x - u_x) \\ \Leftrightarrow u_x &= \frac{\delta}{\lambda R_x + \delta} m_x \end{aligned} \tag{19}$$

The steady state flows into a firm must equal the steady state flows out of a firm:

$$\begin{aligned} \lambda r_{xy} u_x &= \delta e_{xy} \\ \Leftrightarrow e_{xy} &= \frac{\lambda}{\delta} r_{xy} u_x \\ \Rightarrow e_{xy} &= \frac{\lambda}{\lambda R_x + \delta} r_{xy} m_x \end{aligned} \tag{20}$$

Total output is the sum of each match output. Therefore, to maximize steady steady profits the firm chooses the optimal recruiting effort in each worker sub-market. I assume that each firm is relatively small and, therefore, takes the aggregate level of recruitment in the labor market R_x as given. The firm chooses recruitment effort to maximize profits for each worker type:

$$\max_{r_{xy}} \sum_x \frac{\lambda}{\lambda R_x + \delta} r_{xy} m_x yx(1-\beta) - c(x,y) r_{xy}^2 \tag{21}$$

For each labor market there is a first order condition:

$$
\begin{aligned}
[r_{xy}] \quad : \quad & \frac{\lambda}{\lambda R_x + \delta} m_x xy (1-\beta) = 2c(x,y)\, r_{xy} \\
\Leftrightarrow \quad & r_{xy} = \frac{1}{2} \frac{\lambda}{\lambda R_x + \delta} m_x \frac{xy}{c(x,y)} (1-\beta) \qquad (22)
\end{aligned}
$$

Inserting equation (22) in equation (20) yields optimal employment of each labor type at each firm of:

$$
e_{xy} = \frac{1}{2} \left(\frac{\lambda m_x}{\lambda R_x + \delta} \right)^2 \frac{xy}{c(x,y)} (1-\beta) \qquad (23)
$$

C.3 Sorting

Positive sorting or assortative matching results when high type firms hire a large share of high type workers as a portion of their total employment. A sufficient condition to ensure sorting that the derivative of the ratio of employment shares between a high and low productivity firm types increases as worker type increases. Employment share of worker type x in firm type y can be expressed as:

$$
\begin{aligned}
\frac{e_{xy}}{e_y} &= \frac{\frac{1}{2}\left(\frac{\lambda m_x}{\lambda R_x+\delta}\right)^2 \frac{xy}{c(x,y)}(1-\beta)}{\int \frac{1}{2}\left(\frac{\lambda m_z}{\lambda R_z+\delta}\right)^2 \frac{zy}{c(z,y)}(1-\beta) f_x(z)dz} \\
&= \frac{\left(\frac{\lambda m_x}{\lambda R_x+\delta}\right)^2 \frac{x}{c(x,y)}}{\int \left(\frac{\lambda m_z}{\lambda R_z+\delta}\right)^2 \frac{z}{c(z,y)} f_x(z)dz} \qquad (24)
\end{aligned}
$$

where $f_x(z)$ is the density function over worker types. Let $y' > y$, the ratio of employment shares can be expressed as:

$$
\begin{aligned}
\frac{e_{xy'}}{e_{y'}} / \frac{e_{xy}}{e_y} = \frac{e_y}{e_{y'}} \frac{e_{xy'}}{e_{xy}} &= \frac{\int \left(\frac{\lambda m_z}{\lambda R_z+\delta}\right)^2 \frac{z}{c(z,y)} f_x(z)dz}{\int \left(\frac{\lambda m_z}{\lambda R_z+\delta}\right)^2 \frac{z}{c(z,y')} f_x(z)dz} \frac{\left(\frac{\lambda m_x}{\lambda R_x+\delta}\right)^2 \frac{x}{c(x,y')}}{\left(\frac{\lambda m_x}{\lambda_x R_x+\delta}\right)^2 \frac{x}{c(x,y)}} \\
&= \frac{\int \left(\frac{\lambda m_z}{\lambda R_z+\delta}\right)^2 \frac{z}{c(z,y)} f_x(z)dz}{\int \left(\frac{\lambda m_z}{\lambda R_z+\delta}\right)^2 \frac{z}{c(z,y')} f_x(z)dz} \frac{c(x,y)}{c(x,y')}. \qquad (25)
\end{aligned}
$$

A sufficient condition for sorting is that the ratio of shares is increasing in worker type. Taking the derivative with respect to x yields:

$$\frac{\partial^{e_y}/_{e_{y'}}{}^{e_{xy'}}/_{e_{xy}}}{\partial x} = \frac{\int \left(\frac{\lambda m_z}{\lambda R_z+\delta}\right)^2 \frac{z}{c(z,y)} f_x(z)dz}{\int \left(\frac{\lambda m_z}{\lambda R_z+\delta}\right)^2 \frac{z}{c(z,y')} f_x(z)dz} \frac{\partial \frac{c(x,y)}{c(x,y')}}{\partial x}. \tag{26}$$

Therefore, sorting results if the cost function satisfies the following condition:

$$\begin{aligned} & \frac{\partial \frac{c(x,y)}{c(x,y')}}{\partial x} > 0 \\ \Leftrightarrow \quad & \frac{c(x,y')\, c_x(x,y) - c(x,y)\, c_x(x,y')}{\left[c(x,y')\right]^2} > 0 \\ \Leftrightarrow \quad & \frac{c(x,y')\, c_x(x,y)}{c(x,y)\, c_x(x,y')} > 1. \end{aligned} \tag{27}$$

For example, if $c(x,y) = \ln(xy)$ then

$$\frac{c(x,y')\, c_x(x,y)}{c(x,y)\, c_x(x,y')} = \frac{\ln(xy')}{\ln(xy)} > 1 \quad \text{as} \quad y' > y. \tag{28}$$

The general condition is that the cost function must be log submodular. This ensures that high-productivity firms can recruit high-productivity workers at a relatively lower cost. If the cost function is the same as the production function, e.g. $c(x,y) = xy$, then this expression is equal to one and there is no sorting. In this case all firms will have the same worker-skill composition but more productive firms will be larger. If $c(x,y)$ is log supermodular, e.g. $c(x,y) = \exp(xy)$, then it is relatively more costly for high-productivity firms to recruit high-productivity workers and there will be negative assortative matching.

D Effect of Between- and Within-Group Changes in Employment on Changes in Sorting

An important consideration is whether changes in sorting are the result of changes in the relative size of employment shares across groups or due to the changing structure of employment within groups. By "groups" I have in mind industries, firm size groups, and worker flow groups. For example, since export exposure induces an relative increase in the size of the manufacturing sector, the increases in sorting may simply be the result of employment shifts to the manufacturing sector if manufacturing, in general, has a higher level of sorting.

To try to answer this question, I use the structure of my worker flow decomposition. However,

Table A4: Decompostion of the Change in Sorting into Between- and Within-Group Components

	Change in correlation between worker and establishment fixed effects			
	I. Aggregate		II. Export-induced	
	BT-Group	WI-Group	BT-Group	WI-Group
Group definition	(1)	(2)	(3)	(4)
Industry	0.002	0.148	0.0000	0.0094
	(1.57)	*(98.43)*	*(0.06)*	*(99.94)*
Firm Size	0.004	0.144	0.0005	0.0089
	(2.89)	*(97.11)*	*(5.81)*	*(94.19)*
Worker Flow	-0.002	0.149	0.0003	0.0091
	(-1.12)	*(101.12)*	*(3.51)*	*(96.49)*
Industry*Firm Size	0.007	0.142	0.0004	0.0090
	(4.86)	*(95.14)*	*(4.58)*	*(95.42)*
Industry*Worker Flow	0.001	0.129	-0.0003	0.0074
	(0.51)	*(99.49)*	*(-4.87)*	*(104.87)*
Firm Size*Worker Flow	0.003	0.126	0.0004	0.0066
	(2.17)	*(97.83)*	*(6.04)*	*(93.96)*
Industry*Firm Size*Worker Flow	0.006	0.143	-0.0003	0.0098
	(4.28)	*(95.72)*	*(-3.38)*	*(103.38)*

Notes: The contribution of each component as a percentage of the total change is in parentheses. The total change in correlation for aggregate (export-induced) employment changes is 0.158 (0.0093). However, when performing the between-/within-group decomposition the components don't necessarily always add up to the total change in correlation as the decomposition is not strictly addivitely separable. Therefore, in the table, the total change for each row is defined as the within- plus between-group change. "Industry" consists of two groups: manufacturing and non-manufacturing. "Firm Size" consist of three groups: non-continuing firms, continuing firms below the median of the employment-weighted firm size distribution in the initial interval, and continuing firms above the median of the employment-weighted firm size distribution in the initial interval. "Worker Flow" consists of six groups: unemployment to employment, "other" to employment, labor market entry, job stayers, job-to-job between local labor market, and job-to-job within local labor market.

in constructing counterfactual employment in each cell of the joint distribution I break the change in employment into two components. Let k denote a generic "group". Note that employment in the next period $(p+1)$ in each cell of the joint fixed effect distribution (ij) can be decomposed into what I will define as a between- and a within-group component. The between-component produces a counterfactual employment growth for each cell of the joint distribution equal the to the total employment growth for group k across all cell of the joint distribution multiplied by the initial employment share of cell ij from group k. This component capture the case in which employment growth occurs evenly across all cells according to the initial distribution so that the within-group distribution of employment is unchanged. The within-group component is then the remaining employment growth not explained by the between-group employment growth and represents changes in the structure of employment across the joint fixed effect distribution within a group. The following expression formalizes these components:

$$
\begin{aligned}
\pi_{ij}^{p+1} &= \left[\pi_{ij}^{p} + \sum_{k} \frac{\triangle E_{ijk}}{E^{p}}\right] \frac{E^{p}}{E^{p+1}} \\
\pi_{ij}^{p+1} &= \left[\pi_{ij}^{p} + \sum_{k} \left(\frac{\triangle E_{ijk}}{E^{p}} - \frac{\pi_{ijk}^{p} \triangle E_{k}}{E^{p}}\right) + \sum_{k} \left(\frac{\pi_{ijk}^{p} \triangle E_{k}}{E^{p}}\right)\right] \frac{E^{p}}{E^{p+1}} \qquad (29)
\end{aligned}
$$

where the first component represents the within-group component and the second, the between-group component.

To estimate the effect of between- versus within-group components, I follow a similar methodology to the worker flow decomposition as described in Section 4.1. To compute the between component I set the second component of equation 29 equal to zero for all cell of the joint distribution ij and groups k. The difference between change in the correlation with these counterfactual employment cells and the total change in the correlation serves as the estimation of the contribution of between-group changes in employment to the change in sorting.

Table A4 presents the results of this exercise. Panel I shows the results for the aggregate (or total) change in sorting and Panel II shows the results for the exogenous, export-induced portion of the change in sorting only. Results are reported for every possible combination of three group types: industries, firm sizes, and worker flows. Industries are defined broadly as manufacturing versus non-manufacturing. Given that I am using a 2% sample and I need every group to be populated in each local labor market to make consistent inferences, I am restricted to using this broad industry definition. Firm size consists of three groups: non-continuing firms, continuing firms below the median of the employment-weighted firm size distribution in the initial interval, and continuing firms above the median of the employment-weighted firm size distribution in the initial interval. Worker flows consists of six groups: unemployment to employment, "other" to employment, labor market entry, job stayers, job-to-job between local labor market, and job-to-job within local labor market.

The main result of Table A4 is that for all groups the vast majority of the change in correlation is due to within-group changes in the structure of employment across the joint firm and worker fixed effect distribution, rather than the changes in employment levels between groups. This is true for both aggregate employment changes as well is export-induced employment changes. This results suggests that a simple story such as changing employment shares across industries over time is not persuasive explanation for the rise of sorting.

E Effect of Sequencing on Worker Flow Decomposition Results

As in other similar methods, the decomposition method laid forth in 4.1 is potentially sensitive the order in which employment changes of different groups are varied. For example suppose a generic function f depends on e_k^p which represents employment in worker flow categories k at time p. Given six worker flow categories the following would be equally valid represents of the contribution of flow 1 to the total change in f:

$$\hat{\alpha}_1^1 = f\left(e_1^{p+1}, e_2^p, e_3^p, e_4^p, e_5^p, e_6^p\right) - f\left(e_1^p, e_2^p, e_3^p, e_4^p, e_5^p, e_6^p\right)$$

or

$$\hat{\alpha}_1^2 = f\left(e_1^{p+1}, e_2^{p+1}, e_3^p, e_4^p, e_5^p, e_6^p\right) - f\left(e_1^p, e_2^{p+1}, e_3^p, e_4^p, e_5^p, e_6^p\right).$$

In each case only flow one is varying while the other flows are held constant. If the arguments of f are not additively separable, however, there is no guarantee that $\hat{\alpha}_1^1 = \hat{\alpha}_1^2$. In the case that f is a correlation across a joint distribution of employment, the arguments are not additively separable. Therefore, the sequence in which I compute the contribution of worker flows to sorting may matter.

Table A5 reports summary statistics of the results of the worker flow decomposition over all possible sequences for the aggregate changes in sorting and the export-induced changes in sorting. The results can be comparable to results of the main specification reported in Table 5. In this case summary statistics are computed over 32 different sequences. This exercise suggests that the main results are not sensitive to changes in sequencing. Even if we take the share of sorting for labor market entry at the minimum level across all sequences it is still greater than the maximum of any other share. Therefore, the importance of labor market entry is robust to sequencing. This is particularly true for the case of export-induced changes in sorting which shows very little variance with respect to the sequencing of the decomposition.

Table A5: Descriptive Statistics of Worker Flow Decomposition Across Different Sequences

	I. Aggregate				II. Export-Induced			
	Mean	S.E.	Max	Min	Mean	S.E.	Max	Min
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Unemployment to Employment	0.0031	0.00024	0.0052	0.0012	0.00003	0.000001	0.00004	0.00003
	(1.93)	*(0.15)*	*(3.26)*	*(0.77)*	*(0.35)*	*(0.01)*	*(0.41)*	*(0.28)*
"Other" to Employment	0.0152	0.00025	0.0180	0.0130	0.00093	0.000001	0.00094	0.00092
	(9.61)	*(0.16)*	*(11.38)*	*(8.20)*	*(9.92)*	*(0.01)*	*(10.02)*	*(9.83)*
Labor Market Entry	0.0883	0.00090	0.0980	0.0782	0.00448	0.000002	0.00450	0.00445
	(55.71)	*(0.57)*	*(61.85)*	*(49.38)*	*(47.93)*	*(0.02)*	*(48.19)*	*(47.68)*
Job Stayers	0.0203	0.00076	0.0271	0.0143	0.00234	0.000001	0.00235	0.00233
	(12.79)	*(0.48)*	*(17.11)*	*(9.02)*	*(25.08)*	*(0.01)*	*(25.19)*	*(24.97)*
Job-to-Job Between Region	0.0216	0.00036	0.0256	0.0183	0.00156	0.000002	0.00158	0.00155
	(13.63)	*(0.23)*	*(16.15)*	*(11.56)*	*(16.73)*	*(0.02)*	*(16.92)*	*(16.55)*
Job-to-Job Within Region	0.0101	0.00034	0.0135	0.0072	-0.00001	0.000001	0.00000	-0.00001
	(6.35)	*(0.21)*	*(8.49)*	*(4.52)*	*(-0.06)*	*(0.01)*	*(-0.01)*	*(-0.11)*

Notes: The contribution of each component as a percentage of the total change is in parentheses. The total change in correlation for aggregate (export-induced) employment changes is 0.158 (0.0093). There are 32 different sequences by which the six worker flows can be ordered to compute counterfactual employment distributions. "S.E." denotes the standard error across the 32 sequences.