

Cyclical Labor Market Sorting^{*}

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Abstract

We consider sorting in the labor market, that is, whether high or low productivity workers and firms tend to match with each other, and how this varies cyclically using U.S. matched employer-employee data for recent decades. Although there is considerable disagreement in the nature and extent of assortative matching among different methods for ranking workers and firms, we consistently find that the productivity composition of workers and firms moves in opposite directions over the business cycle. During and after recessions, low-productivity workers leave the labor market, while low-productivity firms gain as a share of employment, so positive assortative matching is greatest in magnitude in the early stages of economic contractions. These results are consistent with differences between workers, rather than firms, driving the value of output, which we demonstrate using a model of labor market search.

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1 Introduction

It is commonly said that during and after recessions, overqualified workers get stuck in low-paying jobs. Recent studies such as Kahn (2010) and Oreopoulos, von Wachter, and Heisz (2012), and Abel and Deitz (2016) have provided evidence that college graduates obtain lower-skill jobs than they otherwise would in the wake of labor market downturns. This disconnect between the workers and their best matches was called by Barlevy (2002) the “sully” effect of recessions, who also emphasized that the lower rates of voluntary quits for better employment during labor market downturns result in more time spent in worse matches.

Such a sully effects of recessions contrasts with more conventional “cleansing effect” of recessions (Caballero and Hammour 1994).¹ In the wake of economic downturns, it is generally understood that the least productive jobs (i.e., employer-employee matches) are destroyed. This cleansing mechanism implies that the remaining jobs will be (at least relatively) more productive. There are thus two plausible channels for how economic downturns might affect job match quality. However, little is known about how economic downturns affect the quality distribution of workers and firms, and the sorting of workers between firms.

In this paper, we address the question of cyclical labor market composition and sorting. We use matched employer-employee data to estimate several different methods of ranking workers and firms by their productivity to establish how “labor market sorting” (i.e., the degree to which low vs. high type workers work at low vs. high type firms) varies over the business cycle. We find that, regardless of the ranking method, recessions are times when the employment distribution shifts towards high productivity workers, as low type workers lose their jobs and have difficulty finding new jobs. This “cleansing effect” on the worker distribution is fairly intuitive. Somewhat more surprising are the firm quality dynamics. We find that the firm quality distribution shifts down in recessions, as low productivity firms take a larger share of employment. This “sully effect” on the firm distribution can be rationalized in a model of on-the-job search, as discussed below. We consider the implications of this evidence for models of labor market search.

We present evidence on how labor market sorting varies over the business cycle by drawing on the insights of many contributions concerning sorting in the labor market that exploit the unique properties of universe-level matched employer-employee data. Abowd, Kramarz, and Margolis (1999)

¹Barlevy (2002) considered this margin as well.

exploited a linear framework in which worker productivity is an additive function of a worker effect and a firm effect, which many papers including Card, Cardoso, and Kline (2016) have used as a method of assessing the degree of labor market sorting. More recent work on the degree of sorting in the labor market have introduced two-sided heterogeneity in worker and firm productivity into labor market search models as in Hagedorn, Law, and Manovskii (2017) and Lopes de Melo (2018), and these papers have also proposed algorithms that can be directly implemented on matched employer-employee data to calculate the degree of sorting. Bagger and Lentz (2016) have proposed ranking firms based on the share of hires that come from other employers, with the idea that a firm hiring from another firm (i.e., poaching the worker) indicates that workers prefer the new firm to the old. Furthermore, Bartolucci, Devicienti, and Monzón (2015) and Haltiwanger, Hyatt, and McEntarfer (2018) have proposed ranking firms based on firm-level output and input measures such as profits or revenue labor productivity.

We implement four methods of ranking workers and firms using quarterly matched employer-employee data for 11 U.S. states for the years 1994-2013. Each of these methods involves ordering workers and firms along some univariate ranking, that is, workers and firms are of high or low intrinsic rank. We start with a framework that assumes earnings are an additive function of a worker effect and a firm effect. In addition, we implement ranking algorithms that take into consideration particular models of the labor market. We implement a worker re-ranking algorithm in the spirit of Hagedorn, Law, and Manovskii (2017) and Lopes de Melo (2018). We also rank firms based on the share of hires that come from other employers, following Bagger and Lentz (2016), and, to rank workers in a computationally straightforward manner, we rank them by the fraction of time they spend in nonemployment. Finally, we rank workers based on average worker earnings and firms by labor productivity (revenue per worker, with industry adjustments to capture differences in value added).

Despite the fact that these methods yield different degrees of assortative matching, all these methods of ranking workers and firms yield qualitatively similar movements in the distribution of workers and firms by productivity rank.² Lower productivity workers bear the brunt of labor market down-

²Indeed, papers such as Eeckhout and Kircher (2011) present a fundamental identification problem for measuring whether there is positive assortative matching, negative assortative matching, or neither. While we do not want to suggest that the debate over positive assortative matching is over, the recent work of Bagger and Lentz (2016), Hagedorn, Law, and Manovskii (2017), and Lopes de Melo (2018) certainly indicates movement toward the idea that positive assortative matching might be a reasonable characterization of the labor market. However, these recent attempts to explore labor market sorting rely on the idea that there exists some unidimensional method of ranking workers and firms, and our study follows this framework. Recent work by Şahin et al. (2014) and Lindenlaub and Postel-Vinay (2016) explore multi-dimensional models of worker and firm sorting.

turns, when they are less likely to enter employment and more likely to exit to nonemployment as compared to higher type workers. Thus, recessions are times when the composition of the workforce shifts towards high type workers. By contrast, during economic downturns, there is a buildup of jobs at the lower end of the firm productivity distribution. This is because the “job ladder” shuts down, consistent with the findings of Cairo, Hyatt, and Zhao (2016), Haltiwanger et al. (2017a), and Haltiwanger, Hyatt, and McEntarfer (2018).³ Because the countercyclical shift in the worker distribution toward high-ranked workers occurs somewhat earlier than the shift toward low-ranked firms, the measured correlation between worker and firm ranks increases slightly during recessions.

How can cleansing play such a strong role in cyclical worker composition but not cyclical firm composition? To address this question, we use the model of Lise and Robin (2017), which includes heterogeneous worker and firms, on-the-job search, and aggregate uncertainty (i.e., business cycles), all in a tractable framework. We show that their framework does not automatically generate the cyclical changes in composition that we document. Specifically, the model, evaluated at Lise and Robin’s estimated parameter values, produces countercyclical cleansing movements away from both low-ranked workers and firms. However, when we re-estimate the model to explicitly target the cyclical worker and firm type shares, we find that the model can match the qualitative cleansing and sully patterns with only minor changes in the parameters. Interestingly, in both estimation exercises the match production function is steeply sloped in worker type and relatively flat in firm type.

The main conclusions of the modeling exercise are as follows. First, if worker productivity is the primary determinant of the productivity of a match (i.e., the production function is steeply sloped in worker type), then low-productivity matches will almost always be those with low productivity workers. Then in recessions it will mostly be low productivity workers that lose their jobs, generating our observed pattern of “cleansing” the worker distribution. This conclusion echoes a common result from additive models of worker and firm effects, dating back at least to the seminal work of Abowd, Kramarz, and Margolis (1999), that indicates that worker heterogeneity, rather than firm heterogeneity, drives more of the total variation in wages in the economy.

³Of these papers, ours is most similar to Haltiwanger, Hyatt, and McEntarfer (2018) who consider only one recession and rank workers based on education and firms by within-industry productivity. They find that workers of all education levels move from low productivity to high productivity firms. They also find that, in labor market downturns, workers with lower levels of educational attainment are more likely to exit to nonemployment and less likely to exit nonemployment into employment. However, they do not consider aggregate composition or directly measure the degree of labor market sorting between worker and firm types, instead focusing on the cyclicity of the transition rates.

Second, turning to the firm side, Moscarini and Postel-Vinay (2009, 2012, 2013, 2016) have shown that the sullyng of the firm distribution is consistent with a model where there are heterogeneous firms and on-the-job search. In their model, reduced recruiting during a recession leads to fewer poaching losses for low type firms, allowing them to grow relative to high type firms. This mechanism can operate even if workers are heterogeneous, and even if the differences between firms are small (i.e., when the production function is relatively flat in firm type). Thus, both the worker share and firm share patterns can be understood as product of a production function with more weight on the worker.

2 Data

2.1 Source Data

The Longitudinal Employer-Household Dynamics (LEHD) matched employer-employee data allows us to explore cyclical labor market sorting. These are records of earnings disbursements collected as part of unemployment insurance reporting that cover nearly all private sector employment as well as state and local government workers.⁴ It is possible to use these data to link workers and firms over time. Survey and administrative records sources provide information about worker demographics (age, sex, race, ethnicity, and education), as well as employer information (location, industry, firm size, and firm age). Because different states enter the LEHD microdata at different times, see Henderson and Hyatt (2012), we use a consistent set of eleven states with data available from 1994-2013.⁵

Recent enhancements to the LEHD data have facilitated the measurement of employer-to-employer transitions. We follow the approach to measuring employer-to-employer transitions in Hyatt et al. (2014), Cairo, Hyatt, and Zhao (2016), and Hahn, Hyatt, and Janicki (2017).⁶ This involves considering the set of jobs (i.e., distinct employer-employee combinations) that span two consecutive quarters. A worker’s “dominant job” is the employer at which that worker earns the most among all such consecutive quarter jobs. Following those definitions, when a worker’s dominant employer changes without the worker having a quarter without earnings, the worker undergoes an employer-to-employer transition (also called a job-to-job flow), and if the worker does have a quarter without earnings, then

⁴Note that we do not observe self employment or work for the federal government, so these appear to be flows into and from nonemployment.

⁵These states are California, Colorado, Idaho, Illinois, Kansas, Maryland, Montana, North Carolina, Oregon, Washington, and Wisconsin.

⁶For exact definitions, see Appendix A.

any flows into or from employment are considered flows into and from nonemployment.

This paper takes advantage of a number of recently proposed different strategies to rank workers and firms by their productivity. We draw on these different sources to develop four different methods of ranking workers and firms, which we apply to data that begins with the first quarter of 1994 and ends with the last quarter of 2013. This gives us two labor market downturns to analyze: those associated with the 2001 and 2007-2009 recessions.

2.2 Ranking Workers and Firms

We rank workers and firms in four different ways, roughly following different strands of the literature on labor market sorting.⁷ We provide here a brief overview of each of the methods of measuring the extent and cyclicity of sorting. Note that, for this draft, two estimation methods are estimated on 100% of the data (additive effects, as well as the poaching share and nonemployment), while another two are only estimated on a 1% sample of workers (worker reranking, as well as revenue productivity).⁸ All ranks are calculated on an employment-weighted basis.

We first rank workers using a model that assumes that earnings are an additive function of firm type and worker type. The standard reference is Abowd, Kramarz, and Margolis (1999), who estimate a model in which workers and firms produce wages in a way in which their effects are additive. This method has recently been used by Card, Cardoso, and Kline (2016) to measure the degree of sorting in the labor market. To overcome the fact that we only observe workers at different parts of their life-cycles and this affects the estimated worker effects, we first regress earnings on a set of year-of-birth by quarter-in-time dummies (e.g., born in 1965 and working in the first quarter of 1997). Then, we employ an iterative method to identify worker effects, firm effects, and updated birth cohort by quarter effects.

Second, we apply a technique inspired by the recent work of Hagedorn, Law, and Manovskii (2017) and Lopes de Melo (2018) in response to the inconsistency between the identification assumptions of Abowd, Kramarz, and Margolis (1999) and standard models of labor market search.⁹ This

⁷For additional details, see Appendix B.

⁸We are in the process of conducting a number of exercises where we assess the robustness of the estimates we present in this paper. Estimates on our 1% sample should be treated with appropriate caution.

⁹Readers should note that the random search models proposed by Hagedorn, Law, and Manovskii (2017) and Lopes de Melo (2018) do not consider aggregate uncertainty. Therefore appropriate caution is required in interpreting our cyclical results as they do not have a direct interpretation in the context of a well-defined model. However, we think that the computational strategies proposed by these authors, which make very intensive use of matched employer-employee data,

technique involves initially ranking workers by their average lifetime earnings, but then re-ranking workers who are employed at the same firm to maximize the likelihood that a worker at a firm who is ranked as more productive than another worker actually earns more from that employer. Firms are afterwards ranked by measuring the minimum earnings received by workers of a given productivity type, and then taking the difference between earnings received and this implied reservation wage. Firms with a greater difference between earnings paid and the reservation wage have a greater surplus from a match and are therefore considered to be more productive.

Third, we attempt to rank workers and firms in ways that are very quick to run computationally. We rank firms based on the share of the workers that they hire that come from other firms vs. nonemployment, following Bagger and Lentz (2016).¹⁰ This is a rough metric for how desirable a firm is to work for, which includes nonwage amenities.¹¹ To obtain something that is a similarly fast method for ranking workers, we use the fraction of their careers that they spend in employment vs. nonemployment. We count workers who are more frequently employed as being more productive.¹² Specifically, we regress participation on a set of year of birth by quarter dummies and then rank workers based on the average of the residuals from that regression.

Fourth, we rank workers by their earnings and firms by their revenue productivity. For ranking workers, we use average earnings adjusted for age and time, which also serves as the initial guess of a worker's type in both our additive framework and our reranking method. For firms, we perform a novel method of extracting revenue from the U.S. Census Bureau's Business Register, in the spirit of the recent work by Haltiwanger et al. (2017b).¹³ Measures of labor productivity change discontinuously after the year 2001 due to a fundamental change in the processing of the U.S. Census Bureau's Business Register, so using a crosswalk of firm in continuous operation from 2000 to 2002, we im-

can be helpful in assessing the robustness of our overall findings.

¹⁰Again, appropriate caution is warranted because Bagger and Lentz (2016) do not consider aggregate uncertainty.

¹¹One might want to make sure that firms that do more poaching are in fact poaching from lower ranked firms. A direct method of ranking firms based on which firms are poaching from which was proposed and implemented by Sorkin (2016).

¹²This method has appeared in various labor market sorting papers as a rough proxy for worker quality because workers with less to gain from working might spend less time doing so. Also, we note that although they do not place nearly as much emphasis on direct methods of ranking workers as they do the use of the poaching hire share to rank firms, Bagger and Lentz (2016) employ unemployment duration as a method of ranking workers in Section 4.2.1 of their September 2016 draft.

¹³Our difference from this dataset is that labor productivity is measured at the EIN rather than the firm level, and also that we consider all employee businesses in the Census Business Register, not only the consecutive year business operations that are roughly in scope for the County Business Patterns. We also employ data that goes back to 1994, which is a longer time series than is available in that data source. More broadly, our approach is in the spirit of Bartolucci, Devicienti, and Monzón (2015) and Haltiwanger, Hyatt, and McEntarfer (2018).

pute revenue productivity for the earlier years to smooth the discontinuity. We use this firm-level revenue data to calculate the deviation of a firm from the (employment weighted) industry mean revenue per worker. We then obtain a proxy for firm value added by adding this firm-level measure to industry-level value added per worker as published by the Bureau of Economic Analysis.

3 Empirical Evidence on Composition and Sorting

In this section, we document how the sorting of workers into firms of different types varies over the business cycle. We seek to characterize how the composition of employed workers and jobs, as well as labor market sorting, varies with labor market conditions. We have several outcomes of interest: the share of employment that workers and firms of different types constitute, and the relative frequency of particular combinations of worker and firm types (i.e., the degree of sorting). We also measure the worker flows into and from nonemployment and poaching flows across firms that account for these changes in shares. For these exercises, we characterize the health of the labor market using the difference of the unemployment rate from its H-P trend, as well as the first difference in the unemployment rate: these serve as our cyclical indicators. We present regression results for all four methods of ranking workers and firms, however, to save space we only present figures for the additive worker and firm effects models, and relegate similar figures using the other three methods to Appendix C. For ease of exposition, we frequently rank firms and workers into three terciles: low, middle, and high based on a global ranking of workers and firms into these three groups.¹⁴ We have data from 1994-2013, which allows us to consider two economic contractions: the 2001 and 2007-2009 recessions, as well as the expansions that precede, separate, and follow them.

3.1 Sorting in the Labor Market

Before considering intertemporal variation in composition and sorting, we explore how high vs. low productivity workers and firms are associated with each other, as well as the degree to which the different ranking methods produce worker and firm ranks that agree with each other. To do so, we measure the correlation between worker ranks and firm ranks from each of the four methods, and

¹⁴Note that the use of dummy variables to capture time effects substantially mitigates the time trends toward either the low or high tercile that would otherwise be present in the data. Readers should note that earnings increased rapidly in the late 1990s, when the poaching hire share was also the highest, and the impact of these changes is especially mitigated via the inclusion of time dummies.

present these correlations in Table 1. A sizable literature exists on how these different methods yield different measures of labor market sorting, and so we do not expect perfect agreement.

The different methods of ranking worker and firms are positively correlated with each other, although correlations are generally less than 0.5. The revenue productivity measure has the lowest correlation with other ranking methods.

The different methods yield different correlations in the extent to which high vs. low ranked workers are employed at high vs. low ranked firms. The revenue productivity method produces the strongest correlation, at 0.35, while the poaching share and employment duration model produces the lowest correlation, at 0.22. The reranking and reservation wage method yields a somewhat higher degree of sorting than our additive worker and firm effects method, at 0.24 and 0.33, respectively.¹⁵

3.2 Worker and Firm Composition

Figure 1 shows how the share of employment of workers and firms of different types changes over time.¹⁶ Panel 1(a) shows how the share of worker employment changes over time and during recessions. Overall, the changes in the shares in these terciles are very small, with the share of workers moving up or down by less than 0.002 percentage points over the span of a quarter. A disproportionate amount of the movement occurs around the two recessions, where the share of workers in the highest tercile increases, largely at the expense of the workers in the lowest tercile.¹⁷ This shift away from the

¹⁵The correlation between worker effects and firm effects in the additive model is larger than some early implementations of Abowd, Kramarz, and Margolis (1999) estimators on matched employer-employee data, which suggested that the correlation between worker type and firm type was close to zero. It is of the same order of magnitude but smaller than the recently proposed estimator of Bonhomme, Lamadon, and Manresa (2017), and much smaller than that of Borovičková and Shimer (2018). We view our relatively large correlation as the effect of having a very large number of workers and firms, a relatively lengthy panel, and using quarterly rather than annual data. These reduce the amount of “limited mobility bias” that can drive correlation estimates based on the additive model to zero, see Andrews et al. (2012). We show in Appendix Table C1 that implementing our additive estimator on subsets of the data yields much smaller correlations between worker type and firm type.

¹⁶Recall that worker and firm types are time-invariant, and so all composition changes are due to hires and separations. Results are consistent when using the other ranking methods. See Appendix Figure C1 for workers initially ranked by average earnings, but then re-ranked to ensure that more productive workers at the same firm as less productive workers earn more, Appendix Figure C2 to see the worker shares when ranking workers based on the share of their life-cycle they spend in nonemployment, and Appendix Figure C3 for shares of the workforce when ranked by average firm-level revenue productivity.

¹⁷There is a decrease in the share in the low tercile and an increase in the high tercile that precedes the 2001 recession as well. This is attributable to the strong increase in real earnings in the late 1990s in the U.S., see Hahn, Hyatt, and Janicki (2017). Despite having time dummies for to account for level effects attributable to wages at a particular point in time, the ranking methods that we use generally show entrants as more productive than exiters in the context of this surge in real earnings. Note that the method that uses employment duration does not show this increase, see Panel (a) of Appendix Figure C2, in contrast to the other three methods in which the worker type is essentially a transformation of

lowest worker tercile toward the highest continues for the years following each of the recessions.¹⁸ Panel 1(b) shows changes in the firm distribution by productivity. Again, most of the movements are small, with the distribution by productivity by tercile rarely changing by more than 0.002 percentage points, with the exceptions occurring after the two recessions in our time period. In the context of these recessions, employment shifts away from the high productivity employers and toward the low productivity employers. This shift is at its most rapid in the context of each of the recessions, after which it slows down, but this increased share of workers at low productivity firms takes years to dissipate after each of the two recessions.

Table 2 quantifies how worker and firm composition varies with the unemployment rate including the other three methods of ranking workers and firms. Each specification regresses the outcome of interest on the unemployment rate (either the difference from its H-P trend or its first difference), as well as a linear time trend and season dummies.¹⁹ Although the magnitude and statistical significance varies across the different methods, consistent patterns are evident. When unemployment rises, the share of workers in low ranked firms falls, and the share of workers in high ranked firms rises. A one percentage point change in the difference in the unemployment rate from its H-P trend, in the additive effects model, is associated with a decrease in the share of workers in the lowest ranked tercile, for example, by 0.0317 percentage points, and an increase in the share of workers in the highest rank by 0.0237 percentage points. The largest cyclical worker composition changes are found when workers are ranked by the amount of time they spend in nonemployment. These results are five to ten times larger than the effects that are found when ranking workers on the basis of the wage.²⁰ The worker changes in share are similar for the additive effects model and when workers are reranked following Hagedorn, Law, and Manovskii (2017). The largest firm composition shifts away from high productivity firms and toward low productivity firms are found for the additive effects and poaching hire share methods, and smaller changes are found for the worker reranking and revenue productivity methods of ranking firms. These results suggest that, in the context of labor market downturns, employment shifts away from lower productivity workers toward higher productivity workers, and

worker earnings.

¹⁸This is certainly related to the fact that the labor cycle lags the output cycle. Especially starting with the 1990 recession, U.S. recessions have been associated with “jobless recoveries” in which unemployment does not peak until well after output has begun to increase again.

¹⁹Similar specifications have been used to measure the cyclicalities of job ladders in the labor market by, among others, Haltiwanger et al. (2017a).

²⁰In interpreting this result, it is helpful to note that workers spending time in nonemployment are especially likely to do so during recessions, and so the especially strong relationship is at least partially mechanical.

that employment shifts away from higher productivity firms toward lower productivity firms.

One interesting aspect of these countercyclical build-ups at the low end of the firm type distribution, which is common to all four firm ranking methods that we employ, is that the build-up during the 2001 recession is larger than that of the 2007-2009 recession. This is despite the fact that the latter recession was more severe, both in terms of output and in the associated decline in the health of the labor market. In the next subsection, we document the relative roles of poaching and nonemployment to draw a more complete picture of how this occurred.

3.3 Poaching vs. Nonemployment Margins

These changes in employment shares by type are determined by labor market transitions into and out of nonemployment, as well as across employers.²¹ We show these transition rates in Figure 2.²² Panel 2(a) shows net hires from nonemployment by worker type. Net employment growth declines sharply during recessions for all three types of workers. The 2007-2009 recession has more of a decline in employment than the 2001 recession. However, for high productivity workers, especially in the 2007-2009 recession, their employment did not decline nearly as much as it did for the lower productivity groups. When considering the employment transitions across firms of different types, it is helpful to keep in mind the findings of Haltiwanger et al. (2017a) that firms that are higher-ranked in the job ladder are net poachers, and that low-ranked firms rely disproportionately on nonemployment to obtain their workers. Panel 2(b) shows net hires from nonemployment by firm type. There are level differences between the types of firms, with low type firms having more net hiring from nonemployment than the other two groups. Despite these level differences, the cyclicalities are similar, with net nonemployment hiring falling sharply during the two recessions. Panel 2(c) shows net poaching by firm type. Note that net poaching for each worker type is equal to zero by construction (each employer-to-employer transition contributes exactly one poaching gain and one poaching loss). Low type firms lose workers via poaching flows, and high type firms gain workers throughout the time period, but this movement away from low type firms and toward high type firms slows substantially during recessions.

²¹These transition rates are, of course, much larger than the net changes in shares. The changes in the shares are, of course, given by the differences between the transition rates, normalized by overall employment.

²²Again, we only show charts for our additive effects models. See Appendix Figures C4, C5, and C6 for comparable figures from the other ranking methods.

Figure 2 helps illustrate how the employment composition effect led to a larger build-up at low-type firms in the wake of the 2001 recession than the 2007-2009 recession. Following Haltiwanger et al. (2017), in order to see a counter-cyclical build-up at the low-end of the job ladder, the “poaching margin” must overwhelm the “nonemployment margin.” In other words, the countercyclical decline in the movement of workers from low-type firms to high-type firms must be larger than the decline in nonemployment for low-type firms. In the wake of the 2001 recession, there was relatively little change in the difference in nonemployment hiring for high- vs. low-type firms and so the change in poaching dominages. However, in the 2007-2009 recession the excess nonemployment hiring by low-type firms shut down, mitigating the build-up in the share of employment at low-type firms.

Table 3 quantifies how these transition rates vary with the unemployment rate. All methods show that low productivity workers exhibit greater declines in employment than high type workers, although this difference is lowest for the revenue productivity method. There is less evidence of a differential in the net nonemployment hiring of firms by type. All firms exhibit that a one percentage point increase in the H-P detrended unemployment rate is associated with about a 0.07 to 0.22 percentage point decrease (0.02 to 0.90 using the first difference of the unemployment rate) in the net hiring from nonemployment. Whether low or high type firms decline by more is not consistent across ranking methods, and for most it is not possible to reject the hypothesis that the marginal effects are equal. Higher nonemployment effects for the first difference in the unemployment rate relative to the H-P detrended unemployment rate are likely due to the sharp declines in employment in the wake of recessions, which more closely align to NBER recession dates than the level of unemployment. Also, for all ranking mechanisms the net poaching rate increases for low type firms and declines for high type firms, with this being larger in magnitude for the additive effects and poaching hire share with nonemployment duration having movements that are larger in magnitude than the other two ranking methods.

3.4 Cyclical Labor Market Sorting

Now, we turn from composition to sorting. Figure 3 shows how worker sorting evolves over this time period.²³ These measure the frequency with which workers in the “low,” “middle,” and “high” categories are employed at similarly distinguished types of firms. These shares are as a fraction of

²³Again, we only show charts for our additive effects models. See Appendix Figures C7, C8, and C9 for comparable figures from the other ranking methods.

total employment, and so the share of low-ranked workers in all three firm categories sum to the share of low-ranked workers in Panel 1(a).²⁴ The upward movement in the share of workers at low-ranked firms, which occurs throughout the 2001 and 2007-2009 recessions, is accounted for early on by a decline in the share of low ranked workers at low- and middle-ranked firms, but, in the late stages of as well as after recessions, the share of low productivity workers at high ranked firms declines by more than the middle and high ranked firms. Workers of all types, but particularly middle and high productivity workers, are more likely to work at low productivity firms during and immediately after recessions. This movement of higher-type workers into low-type firms more than offsets the decline in employment of low type workers at low type firms at the outset of each of the two recessions, and so the employment share at low-type firms exhibits countercyclical increases.

Tables 4 and 5 quantifies how this sorting varies with the unemployment rate. Results are consistent in sign across methods of ranking workers and firms, but are similar to the overall changes in the share of workers and firms by productivity terciles discussed previously, with the weakest results found when ranking workers and firms on the basis of average revenue productivity. When unemployment increases, the share of employment at the highest productivity firms decreases, and this is most apparent for the lowest ranked workers. In the method of ranking workers and firms where we rank workers using their nonemployment duration, high-ranked workers increase their share in every firm type category somewhat evenly. Taken as a whole, these results indicate that sorting is most apparent in the early stages of recessions, when lower-ranked workers exit to nonemployment, and are the slowest to move up the job ladder to higher ranked firms.

3.5 Cyclical Correlation Between Worker and Firm Ranks

In order characterize the degree to which sorting varies with the unemployment rate, we also consider the correlation between worker rank and firm rank, and how this varies with the unemployment rate. Regression evidence is shown in Table 6. Higher unemployment is associated with a stronger positive correlation between worker ranks and firm ranks. This relationship is stronger for the first-difference of the unemployment rate, which suggests that the correlation between worker ranks and firm ranks increases sharply during and after recessions.

²⁴Note that the summation is exact prior to seasonal adjustment and the application of the Henderson filter (all nine combination of worker and firm terciles sum to unity) and only approximate afterwards.

3.6 Summary of Empirical Findings

Our novel empirical evidence sheds light on how worker sorting evolves cyclically. During and after recessions, the lowest ranked workers are the most likely to move to or stay in nonemployment, although workers of all types are more likely to move to nonemployment. Likewise during and following recessions, the job ladder shuts down, and so lower ranked firms gain as a share of employment. Throughout the cycle, workers of all types move from lower-ranked to higher-ranked firms. However, when the poaching rate is weak, higher ranked workers are especially likely to work at middle ranked firms.

What is equally surprising is a feature of labor market sorting that is absent from our results: we find no evidence that low-ranked workers move “down” the ladder to lower ranked firms. This is an important observation as some recent production functions used to model the labor market predict that low-ranked workers must be moving down the ladder. While this is one perhaps plausible mechanism for generating positive assortative matching, our findings suggest a mechanism that is perhaps a bit more mundane. Low-ranked workers are the most likely to be in nonemployment after a contraction. During an expansion, low-ranked workers enter the labor market, are disproportionately likely to then be low-ranked, and then take time to move up the ladder. The movement of low-ranked workers up to the top of the job ladder weakens the relationship between worker type and firm type. In the remainder of our paper, we find that we can recover a production function between worker types and firm types in a model of cyclical on-the-job search that can match these cyclical sorting moments.

4 A Model of Heterogeneous Workers and Firms

In this section, we evaluate the ability of a model to fit the facts documented above, focusing on the cyclical changes in worker and firm composition. Before describing the details of the model it will be useful to lay out the intuition.

First, consider the worker distribution. The worker distribution will be cleansed in downturns if the marginal matches tend to be those with low type workers. To take an extreme case, if match output is almost entirely a function of worker type then in a recession the dissolved matches will be almost entirely those with low type workers, as opposed to low type firms. Then the question becomes whether a such a worker-centric production function is consistent with sullyng of the firm

distribution in recessions. We argue that it is, and that it is driven by on-the-job search. Moscarini and Postel-Vinay (2009, 2012, 2013, 2016) have shown that the sullyng of the firm distribution is consistent with a model where there are heterogeneous firms and on-the-job search. In their model, lower recruiting during a recession leads to fewer poaching losses for low type firms, allowing them to grow relative to high type firms. This poaching mechanism can operate under any amount of firm heterogeneity, thus it is consistent with a match output function that is mostly (though not completely) a function of worker type. We will show that this type of production function is the outcome of fitting a model to the data.

We work with the model proposed by Lise and Robin (2017). Their model includes aggregate shocks, worker heterogeneity, firm heterogeneity, and on-the-job search; all ingredients we need. Despite its richness, the model can be fully solved relatively easily. The straightforward solution method allows the parameters to be fit via the simulated method of moments. We briefly describe the main features here, see Lise and Robin (2017) for details.

Time is discrete and goes on forever. There is a fixed mass of workers. Workers are indexed by $x \in [0, 1]$. Firms (jobs) are indexed by $y \in [0, 1]$. Jobs may be vacant or filled. Maintaining a vacant job costs $c(v(y))$, which is exogenous to the firm. When matched with a worker, a job produces flow output $f(x, y, z)$ per period, where z is the productivity shock. Workers search while unemployed, and search with a lower intensity while matched. Search is random, and the number of meetings is determined by a Cobb-Douglas meeting function. Matches are dissolved at an exogenous rate δ . Matches may also dissolve endogenously, as aggregate shocks make existing matches unprofitable or outside offers result in poaching losses.

The aggregate productivity shock z_t evolves exogenously according to, e.g., an AR(1). In period t the aggregate state is summarized by z_t and the distribution of workers across job types y . In terms of within-period timing, at the beginning of each period z changes from z_{t-1} to z_t . Next, exogenous separations occur at rate δ . Endogenous separations also occur, dissolving matches with negative expected surplus. Then, given the aggregate state, firms decide how many vacancies to post. Unemployed and employed workers meet vacancies according to the aggregate meeting function. When a worker and firm meet they decide whether to match and at what wage. Finally, production takes place and wages are paid.

A key feature of the Lise and Robin (2017) model is wage setting. Wages are renegotiated only when one party can credibly threaten to dissolve the match if the wage goes unchanged. This may

occur if the aggregate state changes, changing match production and/or the outside options. It may also occur if the worker receives a job offer from another firm. When a firm meets an unemployed worker, the firm makes a take it or leave it offer of an initial wage. The worker must accept the offer or refuse and remain unemployed. In equilibrium the firm will offer a wage that delivers nothing more than the worker's reservation value, and the firm will extract all the expected surplus of the match. When an employed worker meets a second firm, the two firms are put into Bertrand competition. Each firm will try to offer a wage that barely exceeds the value delivered by their competitor. The outcome is that the worker will end up working for the firm that has the highest match surplus with the worker, and will receive the full value of the surplus with the losing firm.²⁵

Under the wage bargaining outlined above, match surplus is independent of the other equilibrium variables. In particular, let b be the flow value of unemployment, constant across workers and time. Lise and Robin show that match surplus $S(x, y, z_t)$ obeys

$$S(x, y, z_t) = f(x, y, z_t) - b + \frac{1 - \delta}{1 + r} \mathbb{E}_t [\max \{S(x, y, z_{t+1}), 0\}] \quad (1)$$

where $\frac{1}{1+r}$ is the discount factor. In this expression $f(x, y, z_t) - b$ is the single period flow surplus of the match. It consists of match output, less the value the worker would derive from unemployment b . The threat point of the firm is zero, since vacant jobs yield zero expected profit in equilibrium. The expectation on the right hand side of (1) is taken over future values of z_{t+1} . If the surplus is still positive in $t + 1$ the match is still profitable, and yields the continuation value $S(x, y, z_{t+1})$. If the surplus of the match would become negative ($S(x, y, z_{t+1}) < 0$) then the match is dissolved and the continuation value is zero.

It is remarkable that the surplus depends only on z_t and not, e.g., the distribution of workers across firms and unemployment. As Lise and Robin (2017) explain, the split of the surplus will of course depend on distributions, but the total surplus need not. Their wage setting mechanism ensures that surplus is preserved under job-to-job transitions, because the original match serves as the (initial) reservation value of the new match. In addition, the value of unemployment is simple to calculate because the hiring firm takes all the expected surplus. The surplus equation can be solved simply by

²⁵The exception is when the potential poaching firm cannot even offer enough to make an improvement on the worker's current wage. In this case the outside offer is not a credible alternative for the worker, and there is no renegotiation

iterating until a fixed point is found.

With the surplus equation in hand, the model equilibrium is easy to calculate. Most of the equilibrium equations are identities making sure that flows and stocks add up correctly. The reader is referred to Lise and Robin (2017) for further derivations.

4.1 Estimation

Lise and Robin (2017) estimate their model via the simulated method of moments (SMM), targeting 28 moments related to unemployment, vacancy posting, job flows, value added, and dispersion. Importantly, all of their moments can be constructed from publicly available data. However, the restriction to public use data means there are not direct measures of worker types, firm types, and the joint match distribution. Instead, Lise and Robin (2017), roughly speaking, use duration dependence in unemployment to pin down the worker type distribution, the cross-sectional dispersion of value added to pin down the firm type dispersion, and time-series correlations in these objects to infer the production function and matching behavior.

In contrast, our data provides more direct measures of worker and firm composition over the business cycle. In the SMM objective function, we will replace the Lise and Robin (2017) heterogeneity moments with our own LEHD-derived moments.²⁶

4.1.1 Construction of worker and firm shares

For the purposes of estimation we focus on the third ranking schema, nonemployment duration and poaching shares, since these map most cleanly into the model framework and are also cheap to calculate on the model-simulated data. Construction of the model-implied moments is hampered by the computational cost of simulating a large panel of workers and firms on every iteration of the SMM solver. Simulating micro level employment and job flow histories may be feasible, but for the current work we take a simpler approach. In the Lise and Robin (2017) model all workers of a given type have the same expected unemployment duration, and all firms of a given type have the same

²⁶One technical issue turned out to be the number of gridpoints used in estimation. Lise and Robin (2017) use 21 gridpoints for each of the worker and firm type distributions. Matching the cyclical worker and firm share moments using this limited number of grid points turned out to consistently create a weak Beveridge curve, and this was rather robust to different moment selection and weighting strategies. In the estimation results presented here, we use 41 gridpoints for the worker type distribution and 31 for the firm type distribution. Of course, increasing the number of gridpoints in this way increases the time required for estimation.

expected poaching share. We can group the “true” worker and firm types into (population weighted) terciles based on these expected values. This obviates the need to simulate microdata, since the expected unemployment durations and poaching shares are already generated as part of the aggregate simulation.²⁷

Given a parameter guess, we order worker types by their expected unemployment duration. We divide worker types into terciles, based on average shares of *employment*, just as in the data. Symmetrically, we break the firm type distribution into terciles based on poaching share. Then we calculate the relationship of each worker tercile-firm tercile share with the first difference of the unemployment rate, as in column 3 of Table 5. These moments are targeted in addition to the 28 moments Lise and Robin (2017) use. We put a high subjective weight on the LEHD moments to be sure that they are influential in the estimation.

4.1.2 Parameterization

We parameterize the model in the same way as Lise and Robin (2017). The production function has 6 free parameters:

$$p(x, y, z) = z(p_1 + p_2x + p_3y + p_4x^2 + p_5y^2 + p_6xy) \quad (2)$$

The aggregate meeting function is Cobb-Douglas with elasticity 0.5 and efficiency α , to be estimated. The convex vacancy posting cost function is $(1 + c_1)^{-1} c_0 v^{1+c_1}$, where c_0 and c_1 are estimated. Exogenous job destruction δ and the rate of on-the-job search s are also estimated. The worker type distribution is assumed to be Beta, with parameters β_1 and β_2 . Finally, the persistence of aggregate productivity (ρ) and its variability (σ) are also estimated. Thus there are a total of 15 parameters to be estimated.

4.1.3 Results

Table 7 shows our parameter estimates, alongside those of Lise and Robin (2017). For the most part the estimates are qualitatively similar to each other, though estimated matching efficiency is somewhat different.

²⁷Obviously, the drawback here is that the model moments are not constructed in the same way as the data moments. Using true types to group agents in the model probably removes attenuation bias which is in the data. In future work we plan to address these issues. At present, we focus only on the qualitative patterns.

Figure 4 shows the estimated production functions. The Lise and Robin model estimates distribution of worker types, and given the parameters the masses of each type of firm are endogenous. Thus, to compare the production functions from two equilibria we need to normalize the worker and firm distributions. In Figure 4 the production functions are normalized so that each increment along the worker (firm) type axis covers an equal fraction of the worker (firm) distribution. Put differently, the worker and firm populations have been reindexed to be uniform distributions.

It is apparent that both production functions put more weight on the worker type, and are nearly flat in firm type. This is consistent with the intuition outlined above to explain the worker and firm composition dynamics. In unreported work, we tried allowing aggregate productivity shocks to differentially affect different firm types, and allowed for a more flexible specification of the value of leisure. Neither of these extensions significantly changed the estimated production function.

Table 8 shows the LEHD moments. Each β is the coefficient from a regression of a worker tercile or firm tercile share of employment on the first difference of unemployment. For example, β_L^{worker} is the coefficient for the employment share of low type workers. The first column is essentially column 3 of Table 2. The second column is the same quantities, calculated from simulated data using the moments from Lise and Robin (2017). The first thing to notice is that the coefficients are large relative to the data: in their model the match shares are more cyclical than implied by our estimates from matched employer-employee data.²⁸ Second, in the estimation in Lise and Robin (2017), low type firms *decrease* in match share during recessions, while high type firms *increase*. Thus, the Lise and Robin (2017) framework does not match the stylized fact that firm type distribution shifts down in recessions unless we target such moments directly. On the worker side, the model does match the empirical pattern that the worker distribution shifts up. The implied moments from our estimation are in the third column of Table 8. Unsurprisingly, the estimates are closer to the data. They also replicate both the “sullyng” of the firm distribution and the “cleansing” of the worker distribution.

Table 9 shows how the two estimated economies behave with respect to the Lise and Robin (2017) targeted moments. Moments not targeted by the LEHD estimation are in italics. The simulated moments are generally close to each other (and the data), as would be expected when the estimated parameters are similar.

To summarize, the Lise and Robin (2017) framework without targeting our cyclical worker and share moments produces results that are qualitatively similar to the results of our extension along a

²⁸Though the attenuation bias noted above likely plays a role here.

number of dimensions. Requiring the economy to match the LEHD moments changes the parameters slightly, but the implied match production functions are very similar, placing more weight on worker type than firm type. When we target the LEHD moments we successfully reproduce the observed cleansing of the worker distribution and sullyng of the firm distribution in recessions. This can be understood as the product of a match output function that is relatively flat with respect to firm type, so that the Moscarini and Postel-Vinay (2009, 2012, 2013, 2016) mechanism operates on firm shares, but worker productivity dominates the cleansing margin.

5 Conclusion

In this paper, we used a number of recent methods that have been developed for ranking firms, workers, and the degree of sorting in the labor market via direct calculations on matched employer-employee data. Despite the fact that these different methods exist and are often contrasted with each other due to their different findings regarding the nature and extent of sorting, we found that they share common cyclical properties. We find that low-ranked workers are disproportionately affected by labor market downturns, in which their share of the workforce declines as they are less likely to enter employment from nonemployment, and more likely to leave employment to nonemployment than other workers. In contrast, the share of employment in low ranked firms increases during and after labor market downturns. The reason for this is that the job ladder slows down substantially: during economic expansions, high ranked firms rapidly poach workers away from low ranked firms, and so low ranked firms have a low size due to poaching. During economic contractions, both the job ladder and hiring from nonemployment slow, but the job ladder margin dominates in terms of cyclical employment composition at low vs. high ranked firms.

We have presented systematic evidence for the existence of countercyclical assortative matching. Regardless of the method, we find similar patterns. During economic contractions, low ranked workers are more likely to exit to nonemployment from firms of every type. Low ranked workers therefore need to climb the job ladder after recessions. However, high type workers are less likely to exit to nonemployment during contractions and therefore remain at high type firms. Therefore, assortative matching is at its greatest in the depths of recession when the low ranked workers have exited to nonemployment and are no longer at the top of the job ladder. Of course, this comes at the cost of those low ranked workers being nonemployed rather than working.

We estimated a model that can generate these properties. To do so, we employed the Lise and Robin (2017) framework, replicating their complete estimation with the addition of the moments calculated from the LEHD. The estimated production function is qualitatively similar to Lise and Robin (2017), placing greater weight on worker type than firm type.

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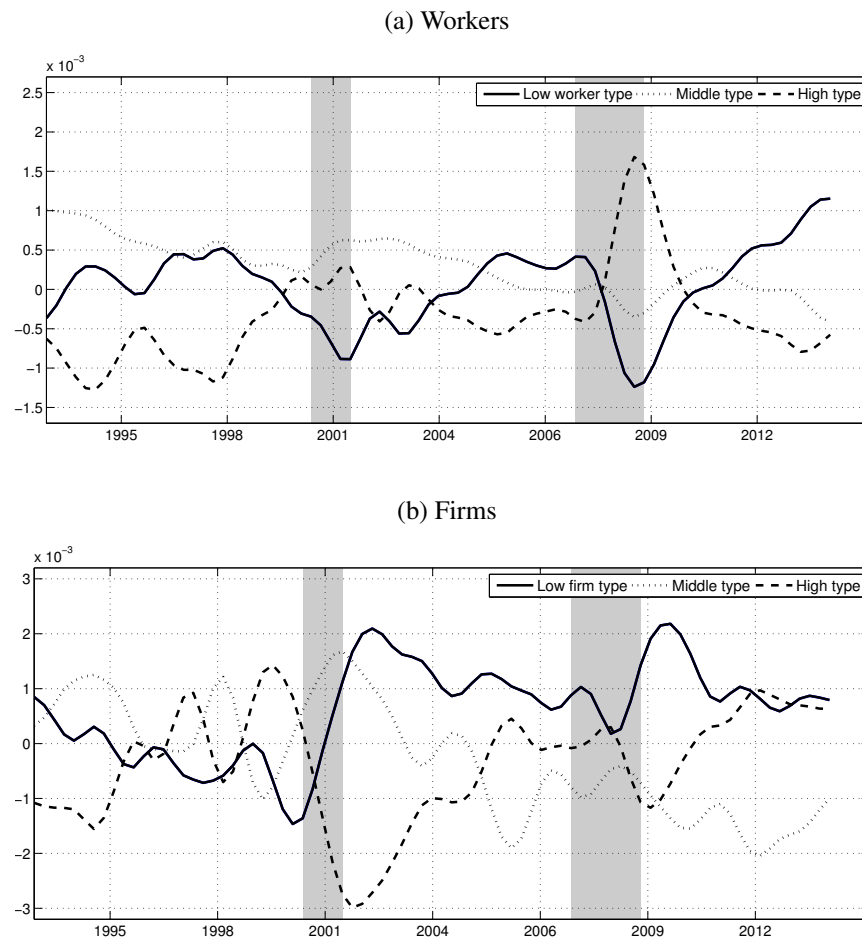
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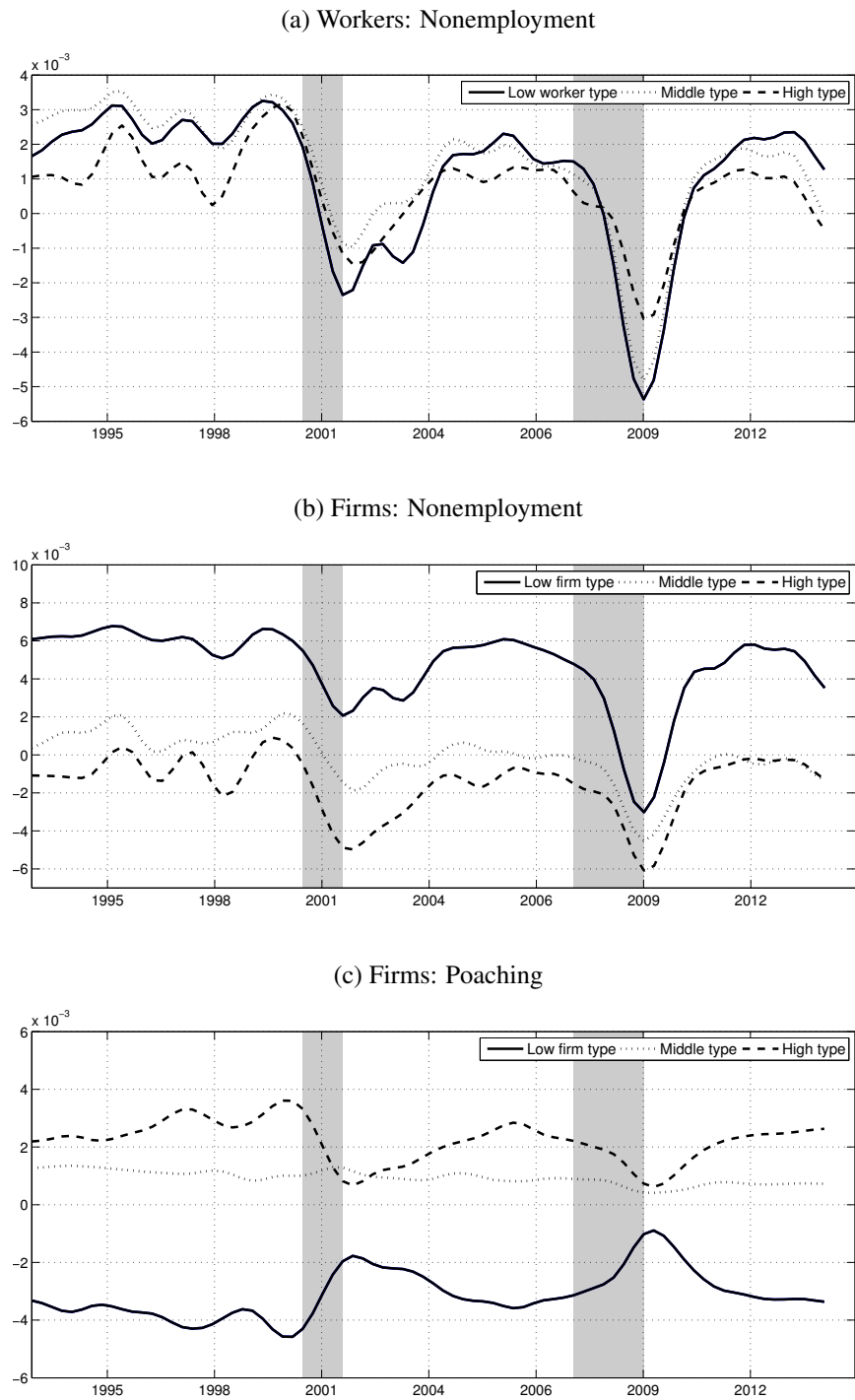
Tables and Figures

Figure 1: Change in Worker and Firm Share, by Productivity Tercile (Additive Model)



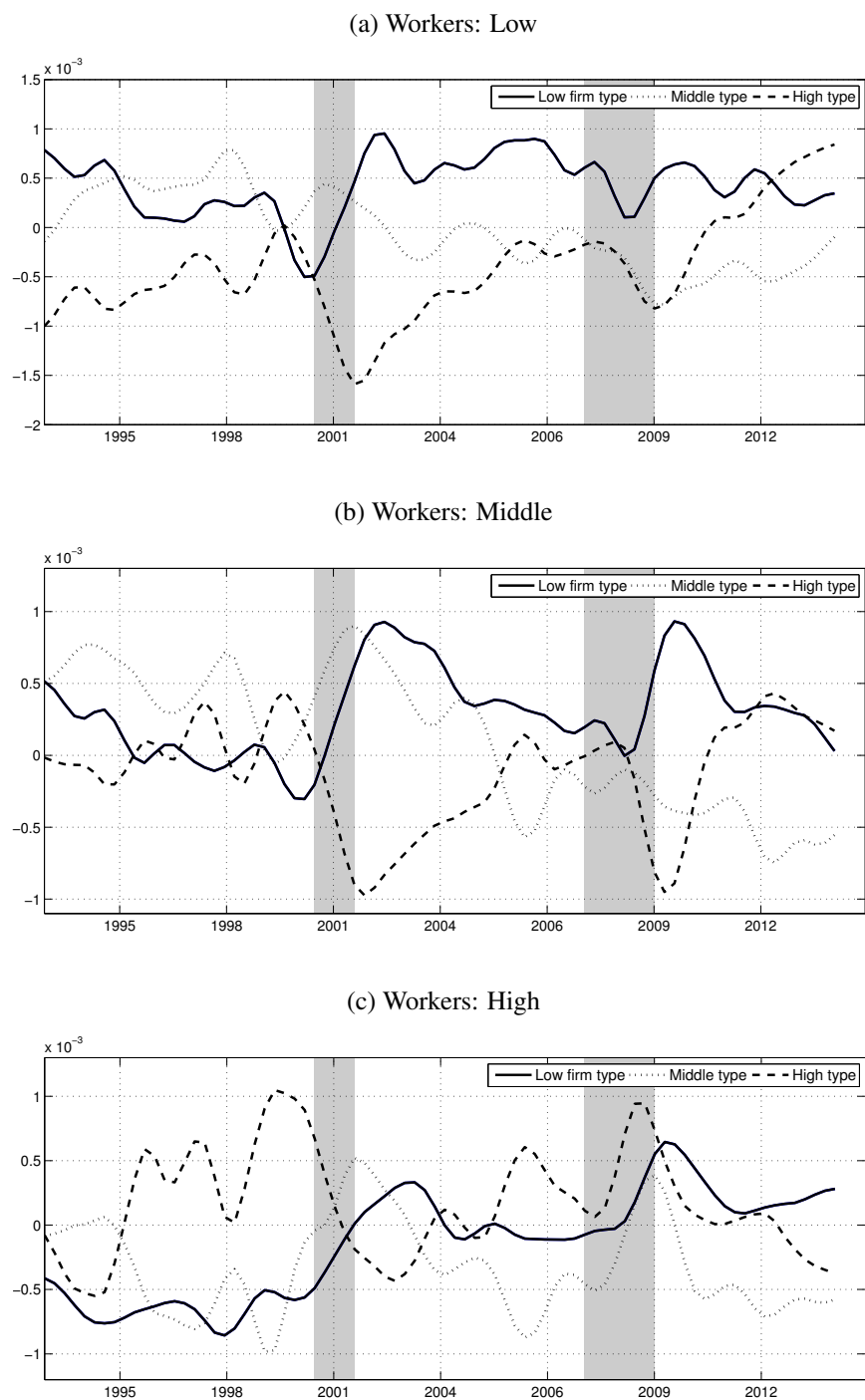
Notes: Productivity terciles calculated off of additive worker and firm effects model.

Figure 2: Net Change in Employment via Nonemployment and Poaching (Additive Model)



Notes: Productivity terciles calculated off of additive worker and firm effects model.

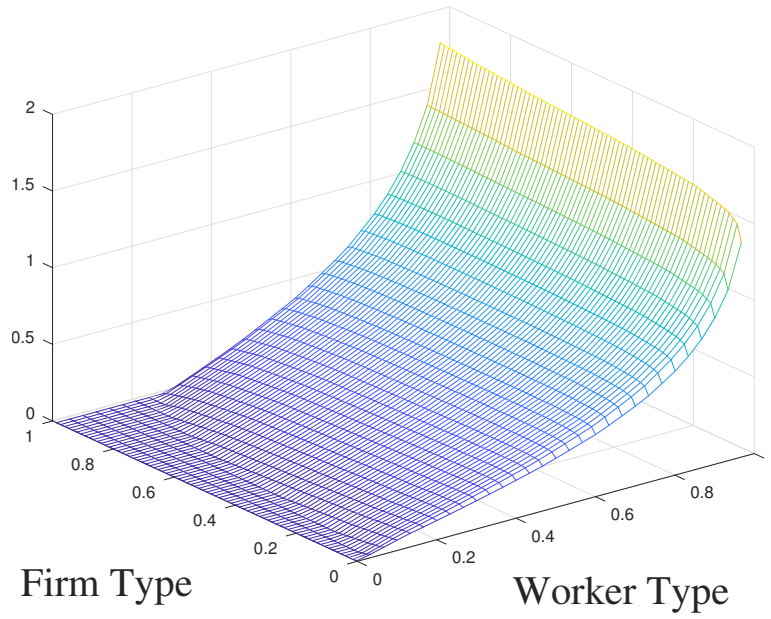
Figure 3: Change in Worker and Firm Share Combinatons by Productivity Tercile (Additive Model)



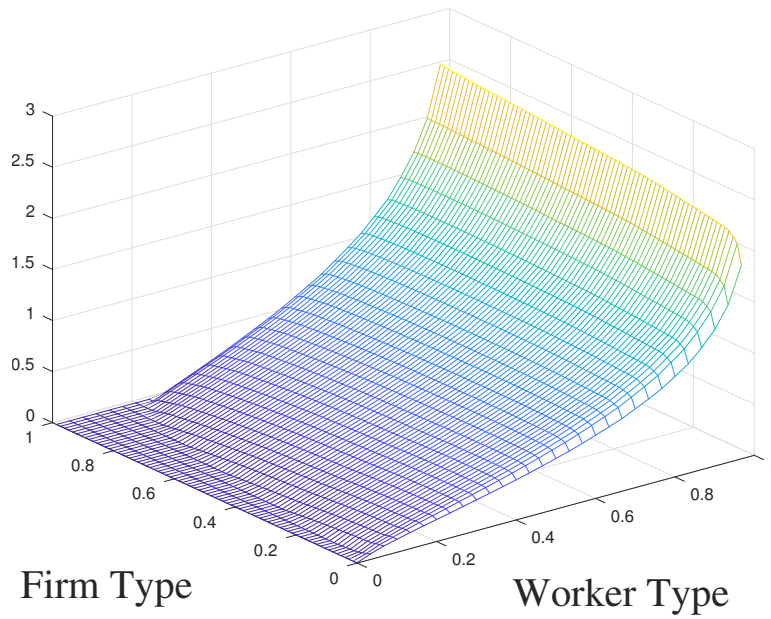
Notes: Productivity terciles calculated off of additive worker and firm effects model.

Figure 4: Model Implied Production Functions

(a) Lise & Robin Estimation



(b) LEHD Moment Estimation



Notes: Worker and firm type distribution normalized to uniforms.

Table 1: Correlation of Worker and Firm Ranks Across Models

	Firm Rankings				Worker Rankings			
	Additive Firm	Surplus	Poaching Share	Revenue Productivity	Additive Worker	Reranking	Employment	Earnings
Firm Rankings								
Additive	1.00							
Surplus	0.77	1.00						
Employment	0.43	0.44	1.00					
Revenue Productivity	0.45	0.55	0.32	1.00				
Worker Rankings								
Additive	0.33	0.49	0.23	0.33	1.00			
Reranking	0.16	0.24	0.13	0.18	0.31	1.00		
Employment	0.16	0.18	0.22	0.14	0.31	0.24	1.00	
Earnings	0.38	0.52	0.24	0.35	0.98	0.79	0.29	1.00

Notes: All correlations are statistically distinct from zero at the 0.0001 significance level.

Table 2: Relationship between Change in Share and Unemployment

	Additive Worker and Firm Effects	Rerank Workers Plus Reservation	Poaching Share and Nonemp.	Revenue Productivity
<i>Difference in Unemployment from HP Trend</i>				
Workers: Low	-3.17** (1.20)	-2.74*** (1.03)	-11.22*** (2.65)	-2.99** (1.40)
Workers: High	2.37** (1.10)	2.21** (0.89)	7.35*** (2.00)	2.09 (1.35)
Firms: Low	5.52*** (1.45)	5.37*** (1.41)	6.30*** (2.20)	5.02*** (1.30)
Firms: High	-6.55*** (1.79)	-7.15*** (1.65)	-6.89*** (1.78)	-4.11*** (1.46)
<i>First-Difference of Unemployment Rate</i>				
Workers: Low	-12.6*** (2.71)	-11.41*** (2.29)	-44.93*** (5.03)	-13.88*** (3.15)
Workers: High	14.82*** (2.18)	12.87*** (1.70)	31.60*** (3.89)	16.90*** (2.72)
Firms: Low	1.95 (3.87)	8.99** (3.62)	11.96** (5.51)	8.18** (3.36)
Firms: High	-8.50* (4.65)	-6.63 (4.46)	-8.90* (4.66)	5.45 (3.72)

Notes: Estimates of change in share of employment on the seasonally-adjusted unemployment rate, season dummies, and a time trend. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively. Standard errors are in parentheses.

Table 3: Relationship between Change in Net Hiring and Unemployment

	Additive Worker and Firm Effects	Rerank Workers Plus Reservation	Poaching Share and Nonemp.	Revenue Productivity
<i>Difference in Unemployment from HP Trend</i>				
Workers: Low	-13.9***	-13.1***	-21.4***	-13.5***
Nonemployment	(2.87)	(2.76)	(5.08)	(3.25)
Workers: High	-7.96***	-8.25***	-1.72	-7.73***
Nonemployment	(2.43)	(2.34)	(1.64)	(2.66)
Firms: Low	-11.9***	-11.9***	-10.2**	-12.2***
Nonemployment	(3.15)	(2.90)	(3.94)	(3.18)
Firms: High	-10.9***	-10.7***	-9.13***	-9.37***
Nonemployment	(2.80)	(2.66)	(2.06)	(2.54)
Firms: Low	6.82***	6.54***	6.03***	7.59***
Poaching	(0.96)	(0.96)	(0.87)	(1.16)
Firms: High	-6.20***	-5.91***	-6.48***	-3.52***
Poaching	(0.94)	(0.94)	(0.97)	(0.79)
<i>First-Difference of Unemployment Rate</i>				
Workers: Low	-51.3***	-48.7***	-83.0***	-56.4***
Nonemployment	(5.46)	(5.27)	(10.00)	(5.96)
Workers: High	-23.0***	-25.6***	-2.75	-27.8***
Nonemployment	(5.78)	(5.44)	(4.03)	(6.07)
Firms: Low	-51.2***	-46.6***	-40.4***	-51.8***
Nonemployment	(5.98)	(5.73)	(8.93)	(6.08)
Firms: High	-35.1***	-33.3***	-30.1***	-30.2***
Nonemployment	(6.34)	(6.07)	(4.48)	(5.80)
Firms: Low	13.65***	14.77***	12.68***	11.88***
Poaching	(2.61)	(2.46)	(2.30)	(3.29)
Firms: High	-12.3***	-11.2***	-12.7***	-8.48***
	(2.52)	(2.55)	(2.61)	(1.95)

Notes: Estimates of change in share of employment on the seasonally-adjusted unemployment rate, season dummies, and a time trend. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively. Standard errors are in parentheses.

Table 4: Relationship between Change in Share and Unemployment (HP)

	Additive Worker and Firm Effects	Rerank Workers Plus Reservation	Poaching Share and Nonemp.	Revenue Productivity
<i>Employed at Low-Type Firms</i>				
Workers: Low	0.89 (0.95)	1.11 (0.67)	-0.66 (1.3)	0.36 (0.99)
Workers: Medium	2.66*** (0.53)	2.43*** (0.69)	4.41*** (0.91)	2.9*** (0.49)
Workers: High	1.98*** (0.49)	1.82*** (0.52)	2.55*** (0.87)	1.76*** (0.53)
<i>Employed at Medium-Type Firms</i>				
Workers: Low	-1.37** (0.54)	-0.82 (0.56)	-3.94*** (1.1)	-1.37 (0.83)
Workers: Medium	0.81 (0.56)	0.94* (0.51)	1.63** (0.68)	-0.34 (0.65)
Workers: High	1.59** (0.74)	1.66*** (0.5)	2.91*** (0.84)	0.8 (0.55)
<i>Employed at High-Type Firms</i>				
Workers: Low	-2.69*** (0.71)	-3.03*** (0.65)	-6.62*** (1.3)	-1.98*** (0.52)
Workers: Medium	-2.66*** (0.63)	-2.84*** (0.55)	-2.17*** (0.67)	-1.66*** (0.44)
Workers: High	-1.2 (0.97)	-1.28* (0.72)	1.89** (0.79)	-0.48 (1.02)

Notes: Estimates of change in share of employment on the seasonally-adjusted unemployment rate, season dummies, and a time trend. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively. Standard errors are in parentheses.

Table 5: Relationship between Change in Share and Unemployment (FD)

	Additive Worker and Firm Effects	Rerank Workers Plus Reservation	Poaching Share and Nonemp.	Revenue Productivity
<i>Employed at Low-Type Firms</i>				
Workers: Low	-0.84 (2.34)	0.93 (1.66)	-8.25*** (3.04)	0.51 (2.42)
Workers: Medium	0.45 (1.49)	3.47* (1.77)	10.44*** (2.25)	4.20*** (1.38)
Workers: High	2.34* (1.29)	4.59*** (1.26)	9.76*** (1.94)	3.47** (1.33)
<i>Employed at Medium-Type Firms</i>				
Workers: Low	-2.68* (1.35)	-5.89*** (1.22)	-18.6*** (1.98)	-10.3*** (1.70)
Workers: Medium	2.44* (1.36)	-0.68 (1.28)	4.67*** (1.65)	-6.12*** (1.44)
Workers: High	6.78*** (1.70)	4.22*** (1.21)	10.84*** (1.83)	2.81** (1.33)
<i>Employed at High-Type Firms</i>				
Workers: Low	-9.09*** (1.58)	-6.45*** (1.65)	-18.1*** (3.05)	-4.08*** (1.30)
Workers: Medium	-5.11*** (1.61)	-4.24*** (1.50)	-1.78 (1.74)	-1.09 (1.16)
Workers: High	5.70** (2.31)	4.06** (1.74)	11.00*** (1.56)	10.62*** (2.17)

Notes: Estimates of change in share of employment on the seasonally-adjusted unemployment rate, season dummies, and a time trend. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively. Standard errors are in parentheses.

Table 6: Relationship between Worker-Firm Correlations and Unemployment

	Additive Worker and Firm Effects	Rerank Workers Plus Reservation	Nonemp and Poaching Share	Revenue Productivity
<i>Difference in Unemployment from HP Trend</i>				
Unemployment (HP)	0.25 (0.18)	0.31*** (0.10)	-0.02 (0.20)	0.30*** (0.05)
<i>First-Difference of Unemployment</i>				
Unemployment (FD)	1.74*** (0.41)	-0.40 (0.25)	1.18** (0.48)	0.44*** (0.13)

Notes: Dependent Variable: Correlation of Worker and Firm Ranks within given model for each quarter. Regression of these correlations for each quarter on the seasonally-adjusted unemployment rate after either HP-filtering or first-differencing, season dummies, and a linear time trend. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are in parentheses.

Table 7: Parameter Estimates

Parameter	Lise & Robin	LEHD Moments
	Estimates	Estimates
α	0.497	0.668
s	0.027	0.026
c_0	0.028	0.03
c_1	0.084	0.08
δ	0.013	0.011
σ	0.071	0.073
ρ	0.9997	0.9997
β_1	2.148	2.577
β_2	12.001	11.27
p_1	0.003	0.003
p_2	2.053	1.998
p_3	-0.140	-0.186
p_4	8.035	8.017
p_5	-1.907	-1.744
p_6	6.596	6.517

Table 8: Cyclical Sorting Moments: Data & Model-Implied

Moment	Data	Lise & Robin	LEHD Moments
		Estimation	Estimation
β_L^{worker}	-44.92	-53.56	-34.25
β_H^{worker}	31.60	26.81	17.61
β_L^{firm}	11.96	-1079.59	30.99
β_H^{firm}	-8.90	348.58	-59.13

Notes: Coefficient β_L^{worker} is the impact of a 1 percent change in the unemployment rate on the employment share of low type workers.

Table 9: Lise & Robin Moments: Data & Model-Implied

Moment	Data	Lise & Robin	LEHD Moments
		Estimation	Estimation
$\mathbb{E}[U]$	0.058	0.059	0.060
$\mathbb{E}[U^{5p}]$	0.035	0.032	<i>0.047</i>
$\mathbb{E}[U^{15p}]$	0.018	0.018	<i>0.041</i>
$\mathbb{E}[U^{27p}]$	0.010	0.011	<i>0.039</i>
$\mathbb{E}[UE]$	0.421	0.468	0.231
$\mathbb{E}[EU]$	0.025	0.028	0.015
$\mathbb{E}[EE]$	0.025	0.025	0.036
$\mathbb{E}[V/U]$	0.634	0.744	1.003
$\mathbb{E}[\text{sd labor prod}]$	0.494	0.505	<i>0.758</i>
$\text{sd}[V]$	0.206	0.105	0.089
$\text{sd}[VA]$	0.033	0.034	0.033
$\text{autocorr}[VA]$	0.932	0.991	0.992
$\text{corr}[V, U]$	-0.846	-0.975	-0.68
$\text{corr}[U, VA]$	-0.860	-0.983	-0.979
$\text{sd}[U]$	0.191	0.203	0.150
$\text{sd}[U^{5p}]$	0.281	0.315	<i>0.152</i>
$\text{sd}[U^{15p}]$	0.395	0.413	<i>0.145</i>
$\text{sd}[U^{27p}]$	0.478	0.439	<i>0.141</i>
$\text{sd}[UE]$	0.127	0.127	0.047
$\text{sd}[EU]$	0.100	0.095	0.159
$\text{sd}[EE]$	0.095	0.112	0.186
$\text{sd}[V/U]$	0.381	0.306	0.220
$\text{sd}[\text{sd labor prod}]$	0.039	0.038	<i>0.036</i>
$\text{corr}[V, VA]$	0.721	0.996	0.749
$\text{corr}[UE, VA]$	0.878	0.978	0.166
$\text{corr}[EU, VA]$	-0.716	-0.910	-0.946
$\text{corr}[UE, EE]$	0.695	0.977	-0.169
$\text{corr}[\text{st labor prod}, VA]$	-0.366	-0.361	<i>-0.458</i>

Notes: Entries in italics are worker and firm dispersion moments which the LEHD moments estimation does not target.

Appendices

A Employment and Transition Definitions

We use 11 states of LEHD microdata that have data available for 1994-2014.²⁹ Our definitions follow the notation established by Abowd et al. (2009), augmented to include job-to-job flows by Hyatt et al. (2014, 2017). The starting point is earnings for individual i from employer j in quarter t , denoted w_{ijt} . If an individual has no earnings from an employer in a given quarter, then the worker did not receive unemployment insurance taxable income from that employer during that quarter, otherwise, if the worker did receive positive earnings from that employer ($w_{ijt} > 0$), then the worker worked for the employer. The following definitions allow us to carefully measure employment and transitions in administrative records that lack start and end dates.

A.1 Employment Concepts

We consider the jobs that span two consecutive quarters (often called “beginning of quarter” jobs). By definition, in such jobs the employee was employed by the employer at the time of the break between the quarters. This employment measure therefore may reasonably be interpreted as indicative of point-in-time employment. Formally, a worker is employed at the beginning of quarter t when

$$b_{ijt} = \begin{cases} 1, & \text{if } w_{ijt-1} > 0 \text{ and } w_{ijt} > 0 \\ 0, & \text{otherwise.} \end{cases}$$

For any two-quarter pair, we disambiguate the data by considering jobs that are maximal earning among all jobs a worker holds at the beginning of quarter t . To do so, the job with the greatest earnings summed across quarter $t - 1$ and t is identified, as follows:

²⁹Note that hours data are not available for any state but Washington for our 11 state set in the analysis time period, and we are not able to release any results for particular U.S. states in this paper.

$$domb_{ijt} = \begin{cases} 1, & \text{if } b_{ijt} = 1 \text{ and} \\ & w_{ijt} + w_{ijt-1} > w_{ikt} + w_{ikt-1} \forall k \\ & \text{s.t. } b_{ikt} = 1 \text{ and } j \neq k \\ 0, & \text{otherwise.} \end{cases}$$

The set of jobs defined in $domb_{ijt}$ are those we use in all of our empirical analysis. Such jobs are unique at the person-quarter level.

A.2 Transition Concepts

We consider transitions between dominant job status across quarters. These are worker movements between employers, as well as into and from nonemployment.

We consider within-quarter transitions

$$wq_{ijkt} = \begin{cases} 1, & \text{if } domb_{ijt} = 1 \text{ and } domb_{ikt+1} = 1 \\ & \text{and } j \neq k \\ 0, & \text{otherwise,} \end{cases}$$

as well as adjacent quarter transitions

$$aq_{ijkt} = \begin{cases} 1, & \text{if } domb_{ijt-1} = 1 \text{ and } domb_{ikt+1} = 1 \\ & \text{and } domb_{ilt} \neq 1 \forall l \text{ and } j \neq k \\ 0, & \text{otherwise.} \end{cases}$$

Flows into persistent nonemployment in quarter t have full-quarter earnings when

$$en2_doms2_{ijt} = \begin{cases} 1, & \text{if } domb_{ijt} = 1 \\ & \text{and } domb_{ilt+1} \neq 1 \forall l \\ & \text{and } domb_{imt+2} \neq 1 \forall m \\ 0, & \text{otherwise,} \end{cases}$$

Flows from persistent nonemployment into employment in quarter t have full quarter earnings when

$$ne2_doma2_{ikt} = \begin{cases} 1, & \text{if } domb_{ikt+1} = 1 \\ & \text{and } domb_{ilt} \neq 1 \forall l \\ & \text{and } domb_{imt-1} \neq 1 \forall m \\ 0, & \text{otherwise,} \end{cases}$$

We also consider workers who did not change jobs, who are called “job stayers.”

$$dombe_{ijt} = \begin{cases} 1, & \text{if } domb_{ijt} = 1 \text{ and } domb_{ijt+1} = 1 \\ 0, & \text{otherwise.} \end{cases}$$

There are, therefore, five transition concepts: two for employer-to-employer transitions, two for transitions into and from nonemployment, and an exhaustive residual for those with dominant employers, job stayers.

B Worker Ranking Implementation Details

We here describe in detail each of our four worker and firm ranking algorithms. Earnings are in logs throughout. Whenever earnings are applied in a ranking method, the earnings concept used in ranking is the same as that used to determine a worker’s dominant employer in Appendix A, that is $w_{ijt} + w_{ijt-1}$.

B.1 Method 1: Additive Worker and Firm Effects

We estimate worker and firm fixed effects via an iterative algorithm. Our goal is to obtain the worker and firm effects that determine earnings w_{ijt} for worker i employed at firm j in quarter t , which are defined via the following formula:

$$w_{ijt} = \theta_i + \psi_j + \xi_{ct}$$

where θ_i is the worker effect, ψ_j is the firm effect, and ξ_{ct} is the effect on earnings of a worker from birth cohort year c at quarter in time t .

We solve for θ_i , ψ_j , and ξ_{ct} for the universe of our 11 states of matched employer-employee data. We first compute the average log earnings of each worker, this is our initial guess $\hat{\theta}_i$ of the worker effect. We then proceed as follows.

1. Estimate the initial firm effects $\hat{\psi}_j = w_{ijt} - \hat{\theta}_i$.
2. Estimate the birth cohort by time effects $\hat{\xi}_{ct} = w_{ijt} - \hat{\theta}_i - \hat{\psi}_j$,
3. Update the worker effects $\hat{\theta}_i = w_{ijt} - \hat{\psi}_j - \hat{\xi}_{ct}$.
4. Update the firm effects $\hat{\psi}_j = w_{ijt} - \hat{\theta}_i - \hat{\xi}_{ct}$.
5. Proceed back to step 2 unless a goodness-of-fit criterion is reached.

We then group each of the employment-weighted firm effects $\hat{\psi}_j$, and the participation-weighted worker effects $\hat{\theta}_i$ into terciles.

B.2 Method 2: Worker Reranking

We implement an algorithm is a simple method of ranking workers and firms that borrows heavily from Hagedorn, Law, and Manovskii (2017) (as does this section), although it is not intended to be a direct replication of this method.

B.2.1 Worker Residuals for Ranking

The first part of our algorithm calculates residual earnings that will then serve as the starting point for the ranking algorithm. We first calculate average log earnings by birth cohort c (specifically, year of

birth) by quarter in time t . We then estimate an initial guess of worker productivity as the deviation of that worker's earnings from the birth cohort by time mean.

B.2.2 Reranking Workers to Minimize Disagreement

We use the rank order of these residuals as the initial guess of a worker's rank, where workers with a higher residual earnings are more productive.

We then look at workers who are employed by the same firm. We evaluate the goodness of fit of our worker ranks as the fraction of the time that a higher ranked worker earns more at a particular firm than a lower ranked worker.

We assume that wage observations are the true wages plus iid measurement error. So the observed wage of worker i at firm k in period t is

$$\hat{w}_{i,k,t} = w_{i,k} + \varepsilon_t$$

where $w_{i,k}$ is the true wage and ε_t is iid noise. Then $n_{i,k}$ is the completed tenure of the worker, the difference in observed wages is

$$\bar{w}_{i,k} - \bar{w}_{j,k} = w_{i,k} - w_{j,k} + \frac{1}{n_{i,k}} \sum_{t=1}^{n_{i,k}} \varepsilon_{i,k,t} - \frac{1}{n_{j,k}} \sum_{t=1}^{n_{j,k}} \varepsilon_{j,k,t}.$$

Suppose that the prior is

$$w_{i,k} \sim \mathcal{N}(\mu_0, \tau_0^2).$$

Then the posterior of $w_{i,k}$, given $\text{Var}(\varepsilon_t) = \sigma^2$ is

$$p(w_{i,k} | \bar{w}_{i,k}, n_{i,k}) = \mathcal{N}(\mu_n, \tau_n^2)$$

where μ_n is the precision-weighted average of the means

$$\mu_n = \frac{\frac{1}{\tau_0^2} \mu_0 + \frac{n_{i,k}}{\sigma^2} \bar{w}_{i,k}}{\frac{1}{\tau_0^2} + \frac{n_{i,k}}{\sigma^2}}$$

and

$$\frac{1}{\tau_n^2} = \frac{1}{\tau_0^2} + \frac{n_{i,k}}{\sigma^2}.$$

We assume an uninformative prior: $\tau_0^2 \rightarrow \infty$. The expressions simplify to

$$\mu_n = \bar{w}_{i,k}$$

and

$$\frac{1}{\tau_n^2} = \frac{n_{i,k}}{\sigma^2}.$$

The “posterior” densities are then

$$p(w_{i,k} | \bar{w}_{i,k}, n_{i,k}) = \mathcal{N} \left(\bar{w}_{i,k}, \frac{\sigma^2}{n_{i,k}} \right)$$

$$p(w_{j,k} | \bar{w}_{j,k}, n_{j,k}) = \mathcal{N} \left(\bar{w}_{j,k}, \frac{\sigma^2}{n_{j,k}} \right)$$

Since everything is independent, the difference in average wages is also normal:

$$p(w_{i,k} - w_{j,k} | \bar{w}_{i,k}, n_{i,k}, \bar{w}_{j,k}, n_{j,k}) = \mathcal{N} \left(\bar{w}_{i,k} - \bar{w}_{j,k}, \frac{\sigma^2}{n_{i,k}} + \frac{\sigma^2}{n_{j,k}} \right)$$

Then we can compute the probability that $w_{j,k} < w_{i,k}$ using the normal CDF:

$$\mathbb{P}(w_{j,k} < w_{i,k}) = \Phi \left(\frac{\bar{w}_{i,k} - \bar{w}_{j,k}}{\sqrt{\frac{\sigma^2}{n_{i,k}} + \frac{\sigma^2}{n_{j,k}}}} \right)$$

The true ranking of workers is given by $\Pi(i, j)$, where $\Pi(i, j) = 1$ if i is (strictly) preferred to j and $\Pi(i, j) = 0$ otherwise. Let $c(i, j)$ be the probability that $\Pi(i, j) = 1$.

If k is the only firm where i and j both worked, then

$$c(i, j) = \Phi \left(\frac{\bar{w}_{i,k} - \bar{w}_{j,k}}{\sqrt{\frac{\sigma^2}{n_{i,k}} + \frac{\sigma^2}{n_{j,k}}}} \right)$$

Otherwise, we set

$$c(i, j) = \prod_{k \in E(i, j)} \Phi \left(\frac{\bar{w}_{i,k} - \bar{w}_{j,k}}{\sqrt{\frac{\sigma^2}{n_{i,k}} + \frac{\sigma^2}{n_{j,k}}}} \right)$$

where $E(i, j)$ is the set of firms that have employed both i and j , and the product symbol should not be confused with the ranking $\Pi(i, j)$.

We estimate Π by choosing $\hat{\Pi}$ to maximize the number of so-defined correctly ranked workers. Specifically, we seek a transitive, complete ordering $\hat{\Pi}$ that solves

$$\arg \max_{\hat{\Pi}} \sum_{j=1}^N \sum_{i=j+1}^N \{c(i, j)\hat{\Pi}(i, j) + c(j, i)\hat{\Pi}(j, i)\}$$

where

$$\begin{aligned} c(i, j) &= \prod_{k \in E(i, j)} \Phi \left(\frac{\bar{w}_{i,k} - \bar{w}_{j,k}}{\sqrt{\frac{\sigma^2}{n_{i,k}} + \frac{\sigma^2}{n_{j,k}}}} \right) \\ \bar{w}_{i,k} &= \frac{1}{n_{i,k}} \sum_{t=1}^{t=n_{i,k}} w_{i,k,t}. \end{aligned}$$

We start with an initial guess and make a single arbitrary move, and check the goodness-of-fit measure to see whether it improves. Our method is as follows:

1. Start with an initial ranking $\hat{\Pi}_0$. Note that i and j are worker names. Any ranking $\hat{\Pi}_n$ implies at function $r_n(i)$, which returns the rank (on $\{1, 2, \dots, N\}$) of the worker i .
2. Starting from a ranking $\hat{\Pi}_n$ choose a random worker name i from $\{1, 2, \dots, N\}$ and a random worker rank r from $\{1, 2, \dots, N\}$.
3. If changing the rank of worker i from $r_n(i)$ to r improves the fit, make this change. Otherwise do nothing.
4. Return to Step 2. Repeat until no more single move rerankings can be made, or some weaker condition is met.

Worker ranks are grouped into three employment-weighted groups: low, middle, and high.

B.2.3 Surplus-Based Firm Ranking

Pool of Nonemployed by Worker Type For each worker, we identify the worker as nonemployed in a given quarter if the quarter falls between the workers' first and last quarters of observed earnings and the worker had zero UI earnings for the quarter. We then sum the total number of nonemployed workers in each quarter for each estimated worker type $\hat{x}$. This corresponds to the pool of unemployed, $u(\hat{x})$, used in the Hagedorn, Law, and Manovskii (2017) IDNoise Algorithm.

The IDNoise Algorithm To address noise in the classification of workers' types, Hagedorn, Law, and Manovskii (2017) propose an algorithm called IDNoise that aims to identify workers whose worker types are particularly unusual given the set of worker types employed by the workers' employers. Hagedorn, Law, and Manovskii (2017) assign these workers with noisy worker types to a set $\hat{\mathbb{N}}$. For each firm j , the IDNoise algorithm identifies $\hat{\mathbb{B}}(\hat{x}, j)$, a set of "cleaned" worker types that the firm hires from nonemployment. The algorithm works as follows for each firm j .

1. Compute the following four firm-specific variables:

- $N(j)$: The number of workers hired from nonemployment by firm j
- $p(\hat{x}, j)$: The number of workers of estimated type $\hat{x}$ hired from nonemployment by firm j
- $\pi(\hat{x}, j)$: The theoretical fraction of workers of type $\hat{x}$ hired from nonemployment by firm j , which is a function of the types of workers that the firm hires and the relative number of this worker-type in the pool of nonemployed workers:

$$\pi(\hat{x}, j) = \frac{u(\hat{x}) \mathbb{1}[p(\hat{x}, j) > 0]}{\sum_{\hat{x}} u(\hat{x}) \mathbb{1}[p(\hat{x}, j) > 0]} \quad (3)$$

- $F(p(\hat{x}, j), \pi(\hat{x}, j), N(j))$: The probability of observing at most $p(\hat{x}, j)$ hires from nonemployment given the probability $\pi(\hat{x}, j)$ from $N(j)$ trials. Assuming that these hires from nonemployment are random draws from the pool of nonemployed workers matching the firm's worker types, $F(p(\hat{x}, j), \pi(\hat{x}, j), N(j))$ is:

$$F(p(\hat{x}, j), \pi(\hat{x}, j), N(j)) = \sum_{i=0}^{p(\hat{x}, j)} \binom{N(j)}{i} \pi(\hat{x}, j)^i (1 - \pi(\hat{x}, j))^{N(j)-i} \quad (4)$$

2. For each worker type $\hat{x}$, initialize $\hat{\mathbb{B}}(\hat{x}, j) = 1$ if the firm hires any workers of that estimated type ($p(\hat{x}, j) > 0$)
3. * for all worker types, $\hat{x}$, with $\hat{\mathbb{B}}(\hat{x}, j) = 1$
 - If the worker type, $\hat{x}$, is the lowest (=1) or highest (=50) worker types and $F(p(\hat{x}, j), \pi(\hat{x}, j), N(j)) \leq 0.1$, then set $\hat{\mathbb{B}}(\hat{x}, j) = 0$ and return to *.
 - For all other worker types, if either $\hat{\mathbb{B}}(\hat{x} - 1, j) = 0$ or $\hat{\mathbb{B}}(\hat{x} + 1, j) = 0$ and $F(p(\hat{x}, j), \pi(\hat{x}, j), N(j)) \leq 0.1$, then set $\hat{\mathbb{B}}(\hat{x}, j) = 0$ and return to *.

After computing the set of types hired by each firm, $\hat{\mathbb{B}}(\hat{x}, j)$, a worker i , with estimated type $\hat{x}(i)$ is assigned to the set $\hat{\mathbb{N}}$ if they are ever employed by a firm j where $\hat{\mathbb{B}}(\hat{x}(i), j) = 0$.

Identifying the Reservation Wage of Each Worker Type When determining the reservation wages of each worker type, we follow Hagedorn, Law, and Manovskii (2017) in excluding the earnings histories of any worker i with a noisy worker type ($i \in \hat{\mathbb{N}}$). The reservation wage for each worker type $\hat{x}$ is calculated using the remaining workers as follows:

1. Construct the set $J(\hat{x})$ which consists of all firms j that hire any worker of type $\hat{x}$ from nonemployment.
2. For each firm $j \in J(\hat{x})$, compute $\bar{w}(\hat{x}, j)$, the average wage paid by firm j to workers of type $\hat{x}$ hired from nonemployment.
3. We define the reservation wage for type $\hat{x}$, $w^r(\hat{x})$, is the 10th percentile of the set of $w(\hat{x}, j)$ where $j \in J(\hat{x})$. Note that Hagedorn, Law, and Manovskii (2017) propose using the minimum average wage as the reservation wage, but we find that this is a very noisy signal, whereas the 10th percentile is smoothly increasing in worker type.

Ranking Firms by Their Average Wage Premium Following Hagedorn, Law, and Manovskii (2017), we rank firms by the product of their average wage premium and their job filling rate. The average wage premium of firm j , $\Omega^u(j)$ is:

$$\Omega^u(j) = \sum_{\hat{x} \text{ s.t. } \hat{\mathbb{B}}(\hat{x}, j)=1} \frac{\frac{u(\hat{x})}{U} (\bar{w}(\hat{x}, j) - w^r(\hat{x}))}{\sum_{\hat{x} \text{ s.t. } \hat{\mathbb{B}}(\hat{x}, j)=1} \frac{u(\hat{x})}{U}} \quad (5)$$

The job filling rate for firm j is a function of the probability that the firm encounters an unemployed worker, M_v , times the probability that the worker's type, $x(i)$, matches the firm's set of acceptable worker types ($\hat{B}(\hat{x}(i), j) = 1$). Since the probability that a firm encounters an unemployed worker is constant across all firms, this is simply a scalar factor in the firm ranking and we thus ignore it. Calculate the probability that the encountered workers' type $x(i)$ matches the firm's set of acceptable worker types, $\tilde{q}^u(j)$, as:

$$\tilde{q}^u(j) = \sum_{\hat{x} \text{ s.t. } \hat{B}(\hat{x}, j)=1} \frac{u(\hat{x})}{U} \quad (6)$$

B.3 Method 3: Poaching Hire Share Plus Nonemployment

Our third method of ranking workers and firms involves ranking methods that can be implemented quickly on administrative records data. Specifically, we rank firms on the basis of the share of hires that come from poaching relative to nonemployment, as higher productivity firms ought to obtain workers from other firms more frequently than lower productivity firms. Workers are ranked on the basis of the amount of time they spend employed, the assumption being that more productive workers are more likely to be employed rather than nonemployed.

B.3.1 Ranking Firms by Poaching Share of Hires

In a manner similar to Bagger and Lentz (2016), we rank firms according to each firm's share of hires that are poached from other firms (as opposed to being hired from non-employment). We begin by identifying the total hires from either employment (EE) or from non-employment (NE) for each firm in the 11 states of the LEHD microdata. These EE and NE hires are identified using the methods described in Hyatt et al. (2014). We include in the EE hires both same-quarter and adjacent-quarter EE transitions. A same-quarter EE transition occurs if the worker has positive earnings from both the previous and the new employer in the transition quarter. An adjacent-quarter EE transition occurs in period t if the worker both has positive earnings from the old employer, but not the new employer, in period t ; and has positive earnings from the new employer, but not the old employer, in period $t + 1$. For the calculation of a firm's NE hires, we exclude all one-quarter recall hires. We define a one-quarter recall hire as a three-quarter employment pattern of employment-to-nonemployment-to-employment, where the worker's dominant employer was the same in the first and last quarter and the worker was non-employed for exactly one full calendar quarter in between.

We estimate each firm's poaching share as the ratio of hires from other employers (EE) to total hires (the sum of EE and NE hires). Firms are then rank ordered into 50 bins according to their poaching share.

B.3.2 Ranking Workers by Prime-Age Employment Rates

We rank workers by their prime-age quarterly employment rate relative to the average employment rate for individuals born in the same year. For each worker, we construct a 0-1 employment indicator variable for every quarter that the worker is between the ages of 25 to 55 (inclusive). This employment indicator variable is set to one if the worker had positive earnings in that quarter and to zero if they were non-employed for the entire calendar quarter.

We then divide workers into cohorts according to their year of birth. For every quarter, we compute the average employment rate of each birth cohort as the average of the employment indicator for all individuals in that birth cohort in the given quarter. For every quarter in which a worker is between the ages of 25-55, we calculate the deviation of the worker's employment indicator from the birth-cohort average employment rate for the given quarter. The worker's prime-age employment rate is simply the sum of the worker's deviations from the birth-cohort average divided by the number of observed quarters in the LEHD micro data for which the worker was between the ages of 25-55. The worker ranking is determined by a rank ordering of workers into 50 bins according to their prime-age quarterly employment rate.

B.4 Method 4: Averages of Earnings, Revenue Productivity

B.4.1 Ranking Workers Based on Average Earnings

In our fourth method, we rank workers in a way that is motivated by the fact that high type workers may exhibit higher average earnings. We simply rank workers by the average of their residual earnings after controlling for age and time-period fixed effects. Note that this is the initial guess of a worker's type in our additive model (Method 1) and our reranking workers and surplus approach (Method 2).

B.4.2 Ranking Firms Based on Revenue Productivity

We use revenue data from the U.S. Census Bureau’s Business Register to measure labor productivity, i.e., revenue-per-worker. We use all available revenue data from 1994-2014.³⁰ These revenue data are annual totals. Multiple observations of revenue data are available for each business in each calendar year, and we use revenue data either from the first year with a reported amount, as well as the second year that a recorded amount is available, with priority given to the latter. These data are Winsorized at both the top and bottom 1% of the revenue distribution. We merge these revenue data using the firm identifier applied to the LEHD data as described in Haltiwanger et al. (2017b).

Imputation of Missing Revenue Data

Not all businesses have revenue data in all years. In some cases, a crosswalk was not available between the LEHD employer data and the Business Register (i.e., missing firm identifier), and in others revenue data was missing from the Business Register. We therefore impute these data elements when they are missing, assuming that they are missing-at-random within quarter firm industry, size, and age categories.

Specifically, we assume that revenue is the following linear function of log firm size and age, estimated separately by quarter and four-digit NAICS code:

$$lp = \beta_0^a + \beta_1^a * firmsize + \beta_2^a * firmage + \beta_3^a * firmsize * firmage + \beta_4^a * firmsize^2 + \beta_5^a * firmage^2$$

where lp is log labor productivity, $firmage$ is log firm age, and $firmsize$ is log firm size.

Imputation for Longitudinal Consistency

The distribution of the Business Register revenue data shifts discontinuously upward around the year 2002, when the Business Register was redesigned. This is because additional data elements concerning revenue became available and more accurate totals are available. Since we do not want the firms in more recent years to appear more productive simply because of a change in reporting, we also implement a simple imputation. The revenue data for 2000 is all provided under the old regime, that for 2002, all under the new, and the year 2001 is a mix of old and new. We therefore take all businesses that existed in the year 2000 and 2002 and use this as training data for imputation of

³⁰Recent work by Haltiwanger et al. (2017b) uses the same source data to create firm-level measures of labor productivity for a shorter set of years, and only for a subset of industries.

$$lp_n = \beta_0^b + \beta_1^b * lp_o + \beta_2^b * lp_o^2 + \beta_3^b * firmsize + \beta_4^1 * firmage + \beta_5^b * firmsize * firmage + \beta_6^b * firmsize^2 + \beta_7^b * firmage^2$$

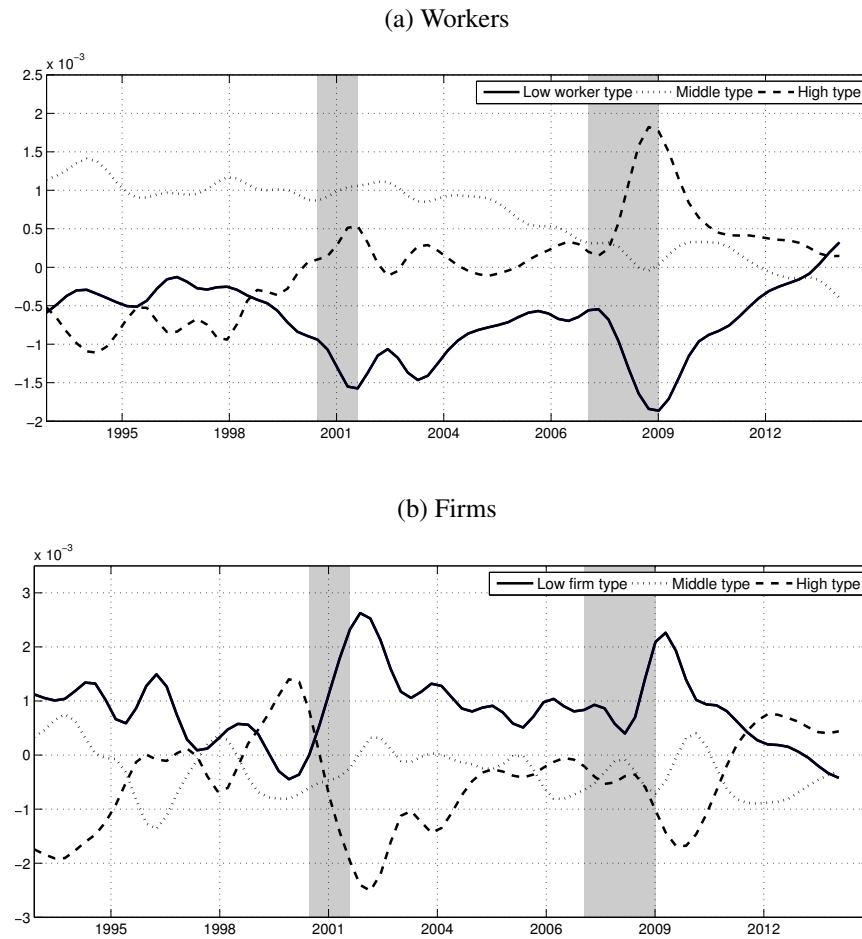
where lp_n is 2002 revenue data and lp_o is revenue data from the year 2000 or earlier.

B.4.3 Ranking Firms

Having attached revenue to all firms in the LEHD data, we proceed in a simple manner to produce ranks firms based on revenue. We rank firms based on the residual firm productivity from year of entry by quarter by industry dummy variable regression. We then add this residual to the value-added per worker data as published by the Bureau of Economic Analysis to obtain a proxy for firm-level value added per worker. We then rank firms based on the average of this sum, over time.

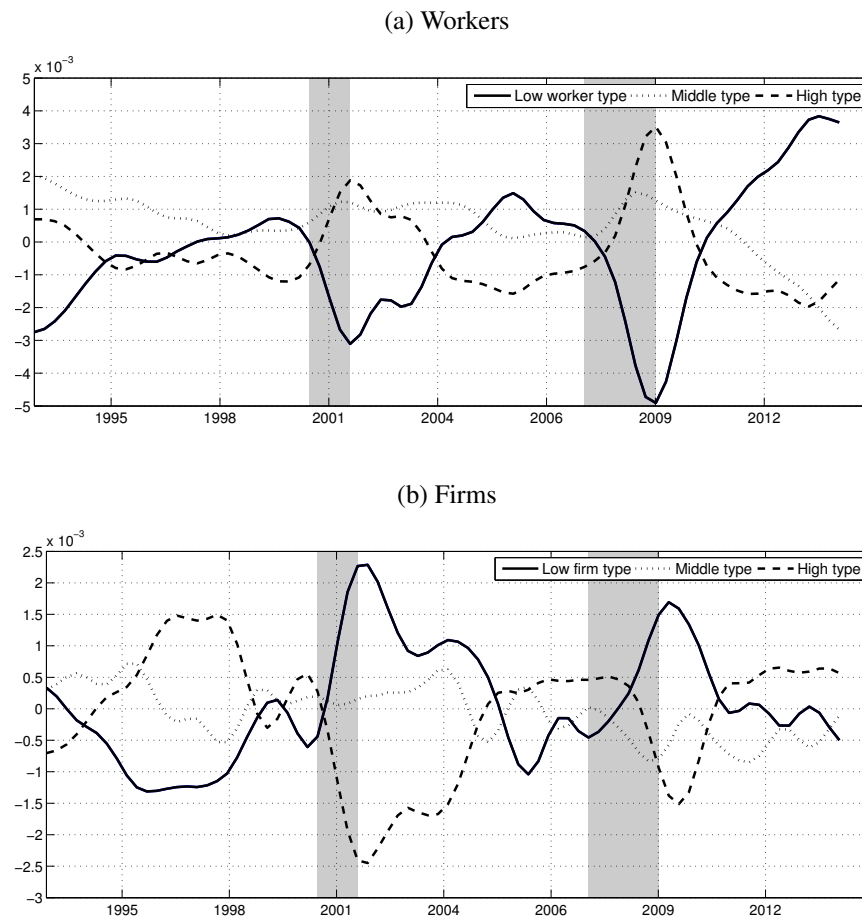
C Supplemental Tables and Figures

Figure C1: Change in Worker and Firm Shares, by Productivity Tercile (Reranking)



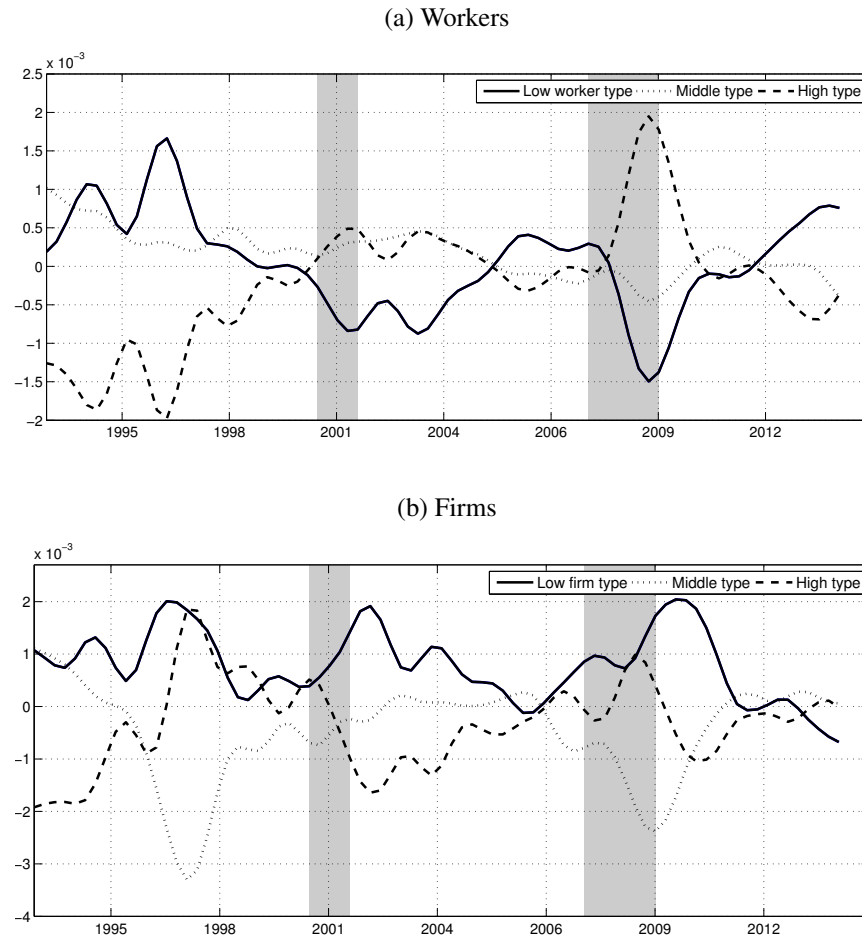
Notes: Productivity terciles calculated off of worker reranking model.

Figure C2: Change in Worker and Firm Shares, by Productivity Tercile (Poaching Hire and Nonemp.)



Notes: Productivity terciles calculated off of nonemployment and poaching hire share model.

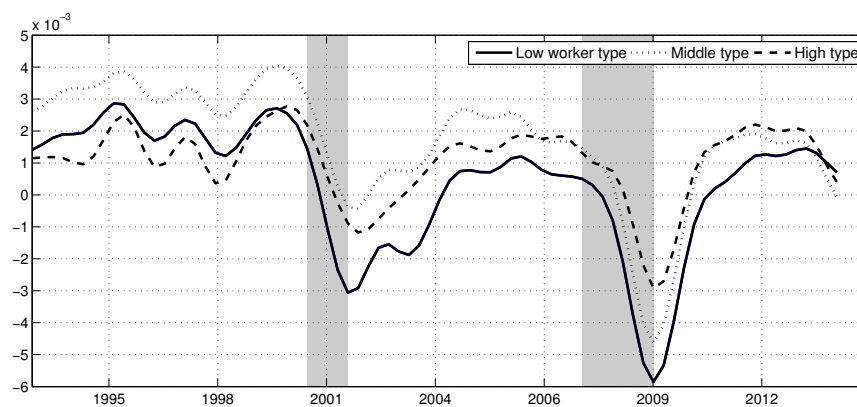
Figure C3: Change in Worker and Firm Share, by Productivity Tercile (Revenue Productivity)



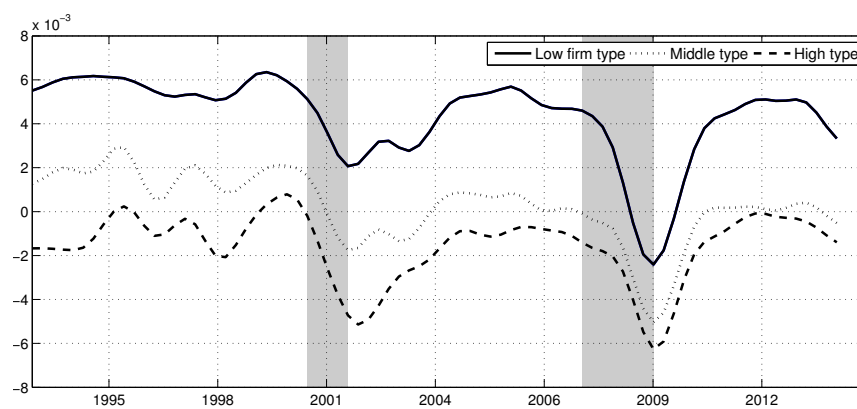
Notes: Productivity terciles calculated off of average revenue productivity.

Figure C4: Net Change in Employment via Nonemployment and Poaching (Reranking)

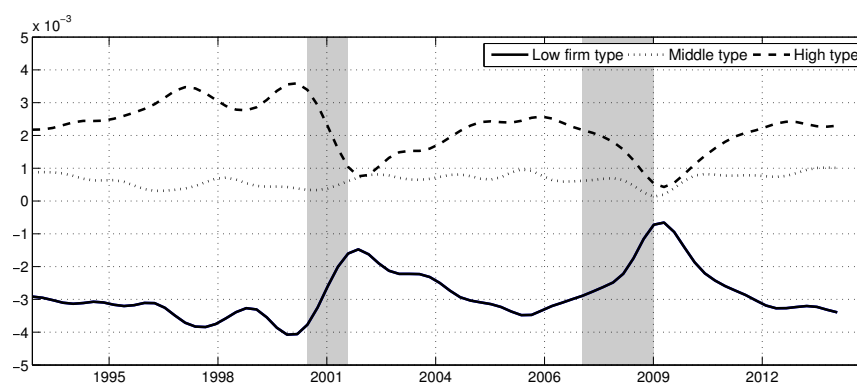
(a) Workers: Nonemployment



(b) Firms: Nonemployment

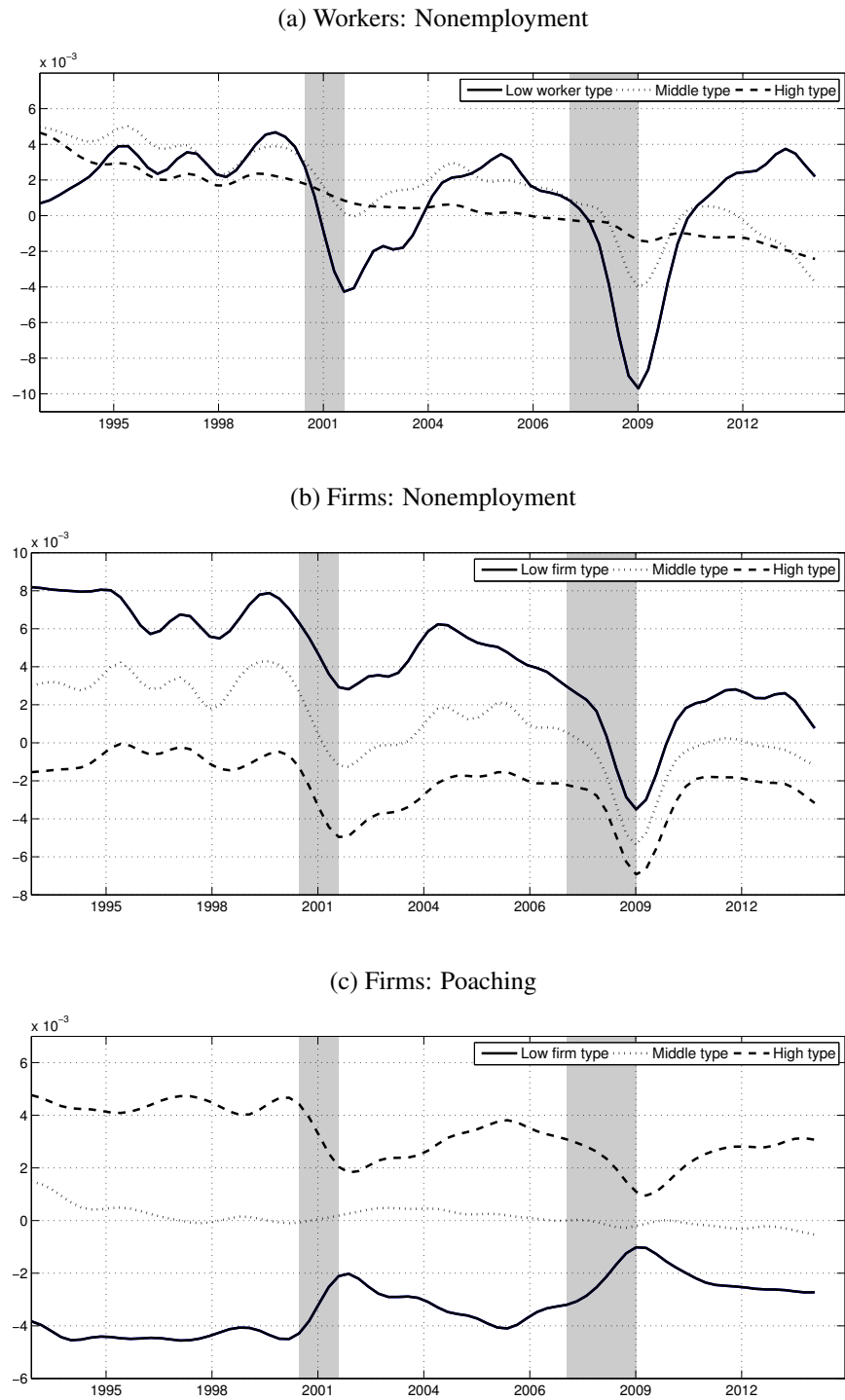


(c) Firms: Poaching



Notes: Productivity terciles calculated off of worker reranking model.

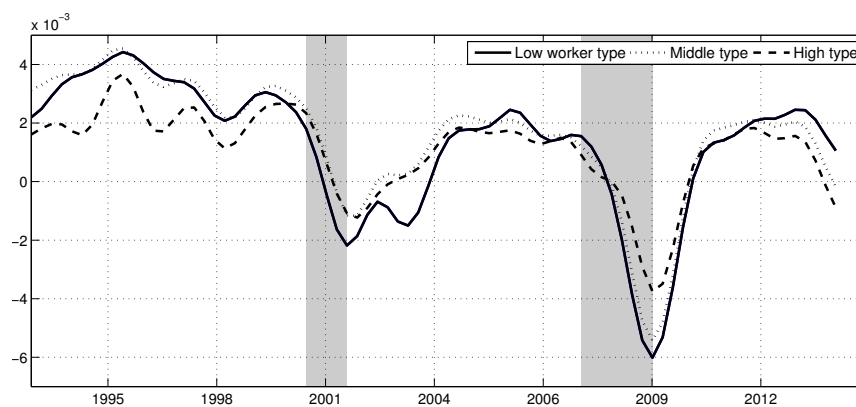
Figure C5: Net Change in Employment via Nonemployment and Poaching (Poaching Hire and Nonemp.)



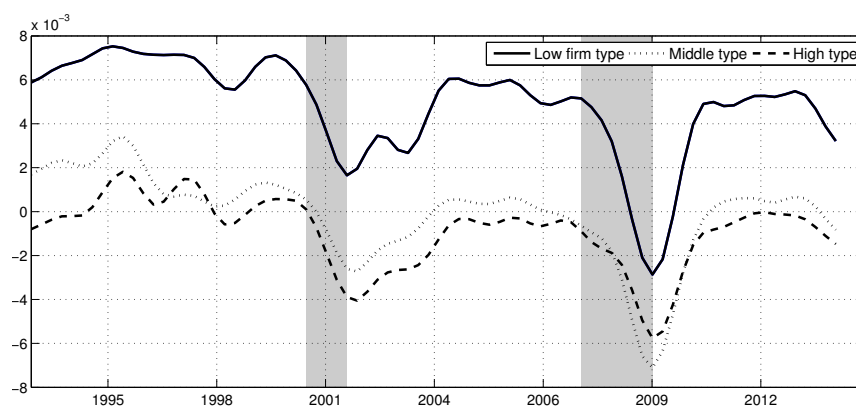
Notes: Productivity terciles calculated off of nonemployment and poaching hire share model.

Figure C6: Net Change in Employment via Nonemployment and Poaching (Revenue Productivity)

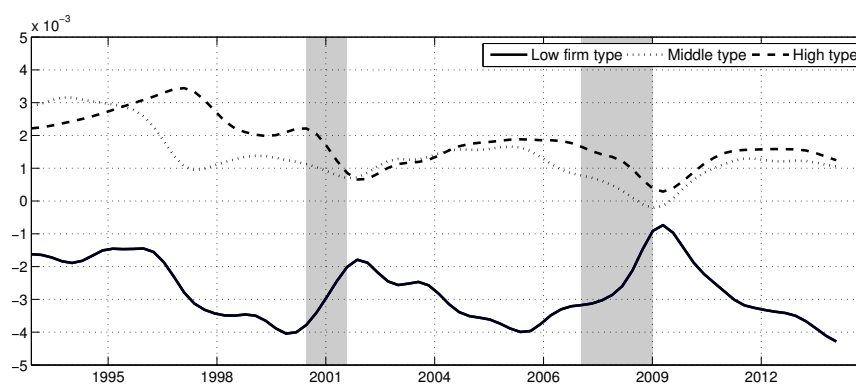
(a) Workers: Nonemployment



(b) Firms: Nonemployment

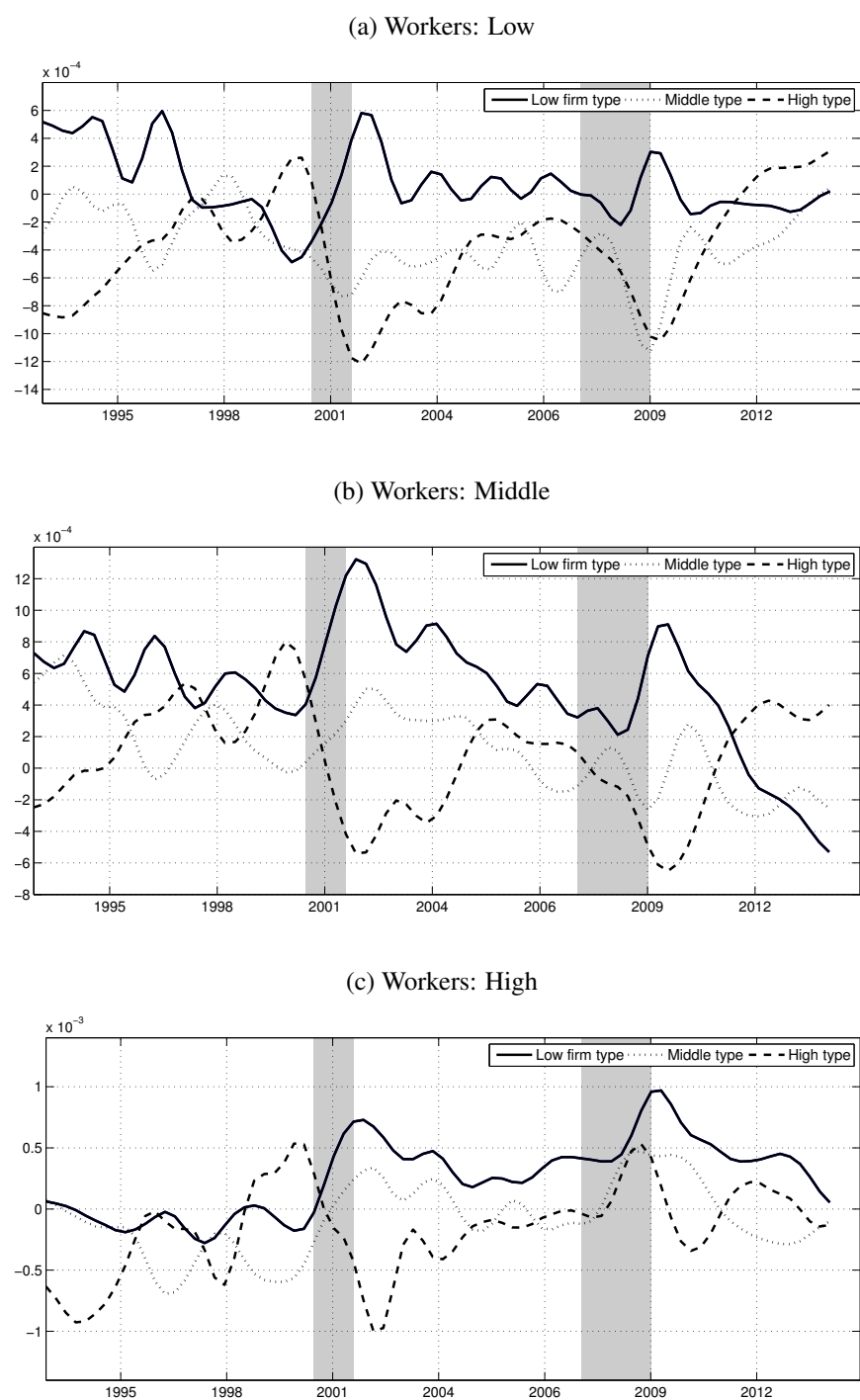


(c) Firms: Poaching



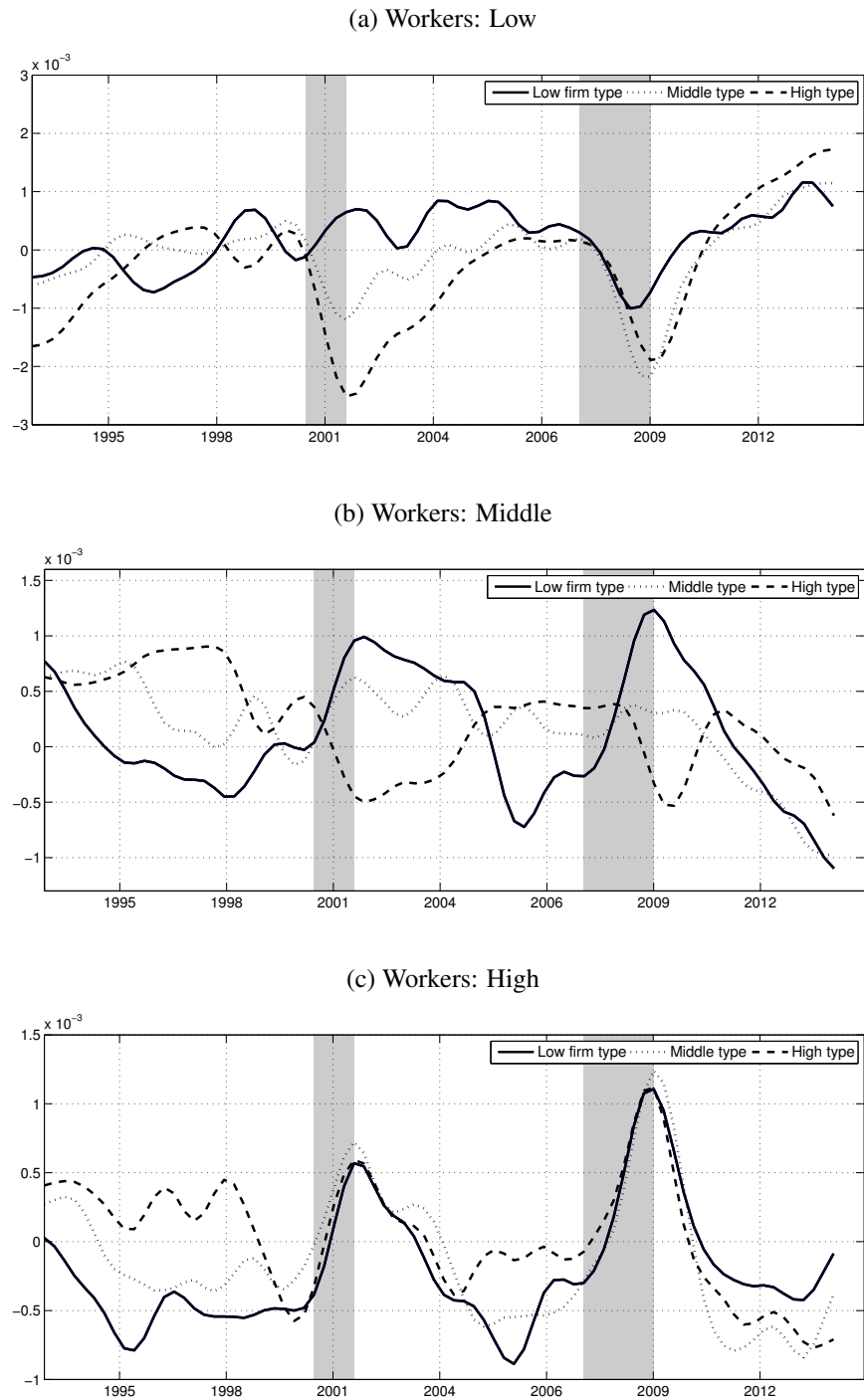
Notes: Productivity terciles calculated off of average revenue productivity.

Figure C7: Change in Worker and Firm Combination Shares, by Productivity Tercile (Reranking)



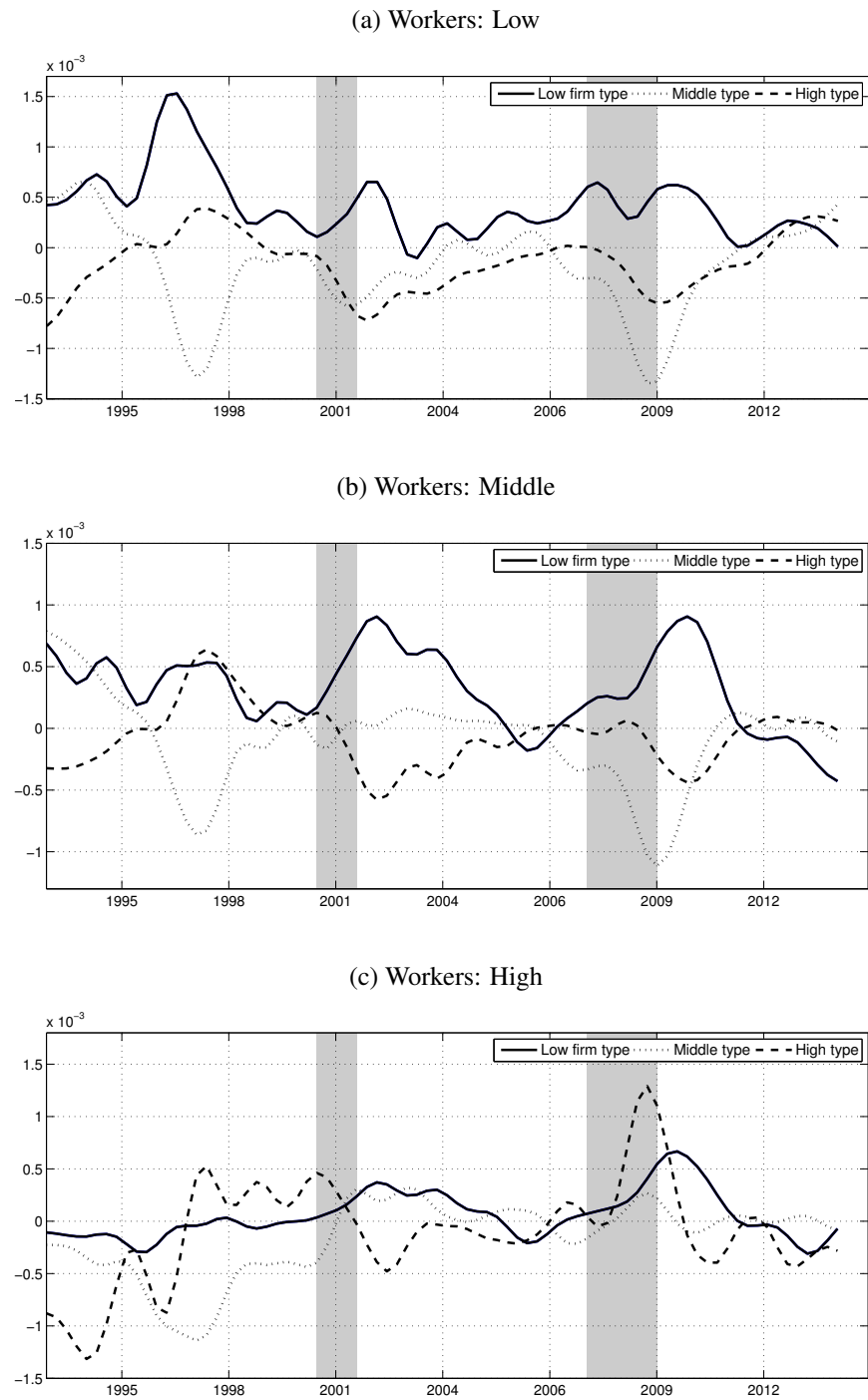
Notes: Productivity terciles calculated off of worker reranking model.

Figure C8: Change in Worker and Firm Combination Shares, by Productivity Tercile (Poaching Hire and Nonemp.)



Notes: Productivity terciles calculated off of nonemployment and poaching hire share model.

Figure C9: Change in Worker and Firm Share Combinatons, by Productivity Tercile (Revenue Pro-ductivity)



Notes: Productivity terciles calculated off of average revenue productivity.

Table C1: Correlation of Worker and Firm Ranks Across Implementation Models

Correlation	0.312	0.326	0.165	0.159	0.176
Control Variables					
Age Quadratic and Time FE	-	Y	Y	Y	Y
Birth Year * Time FE	Y	-	-	-	-
Random Sample					
10%	-	-	-	Y	Y
100%	Y	Y	Y	-	-
Outliers					
20+ Quarters	-	Y	-	-	-
Time Range					
1994-2003	-	-	Y	Y	-
2004-2013	-	-	-	-	Y
1994-2013	Y	Y	-	-	-

Notes: All correlations are statistically distinct from zero at the 0.0001 significance level.