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 matched employer-employee data for recent decades in the U.S. Although there is considerable disagreement in the nature and extent of assortative matching among different methods for ranking workers and firms, we find substantial similarity on how sorting evolves over the business cycle. Although the magnitudes differ across ranking methods, 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. Using the simulated method of moments, we estimate a model with aggregate uncertainty, heterogeneous workers and firms, and on-the-job search, which is able to reproduce these patterns qualitatively.

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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 "sullying" 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.

Barlevy (2002) also considered the more conventional "cleansing" effect of recessions. 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 "sullying 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) 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 Lopes de Melo (2016) and Hagedorn, Law, and Manovskii (2016), 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 (2016) have proposed ranking firms based on firm-level output and input measures such as profits or revenue labor productivity.

We employ four methods of ranking workers and firms using 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 Lopes de Melo (2016) and Hagedorn, Law, and Manovskii (2016). 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 and firms based on revenue productivity.

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.[1] Lower productivity workers bear the brunt of labor market downturns, 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

[1] Indeed, 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 Hagedorn, Law, and Manovskii (2016), Lopes de Melo (2016), and Bagger and Lentz (2016) 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 some unidimensional method of ranking workers and firms, and this study follows that assumption. Recent theoretical work by Şahin et al. (2014) and Lindenlaub and Postel-Vinay (2016) explore multi-dimensional methods of ranking workers and firms, but the multi-dimensional sorting and mismatch literature is much more in its infancy.

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 Kahn and McEntarfer (2014), Haltiwanger, Hyatt, and McEntarfer (2015, 2016), and Cairo, Hyatt, and Zhao (2016).[2]

What kind of a model can rationalize these patterns? We start from the model of Lise and Robin (2016), which includes heterogeneous worker and firms, on the job search, and aggregate uncertainty, all in a tractable framework. We show that the model, as estimated in their paper, does not produce worker/firm share dynamics similar to what we document in our matched employer-employee data. We re-estimate the model (using the simulated method of moments) adding our moments to those targeted by Lise and Robin (2016). The model is then better able to replicate the patterns we document, although matching those additional moments also produces a very weak Beveridge curve.[3]

Focusing on the worker and firm shares, the basic story can be understood as follows: If worker productivity is the primary determinant of the productivity of a match, 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.

Turning to the firm side, Moscarini and Postel-Vinay (2009, 2012, 2013, 2016) have shown that the sullying 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. 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]Of these papers, ours is most similar to Haltiwanger, Hyatt, and McEntarfer (2016) 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 cyclicality of the transition rates.

[3]More work is needed to understand why matching our moments takes the model away from the conventional Beveridge curve.

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 (2016).[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 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.

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

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

[6]For exact definitions, see Appendix A.

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 cyclicality 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 (2015) 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 (i.e., born in 1965 and working in the first quarter of 1997). Then, we employ an iterative method to identify worker and firm effects, ranking these residuals from the birth cohort by quarter deviations.[9]

Second, we apply a technique inspired by the recent work of Lopes de Melo (2016) and Hagedorn, Law, and Manovskii (2016).[10] This 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

[7]For additional details, see Appendix B.

[8]We 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.

[9]If we estimate the birth cohort by quarter effects simulatenously with the worker and firm effects, but omit dummy variables for quarters over time, we find that the worker effects trend upward strongly over time. In this paper, we are investigating the extent of labor market sorting and how it changes over time. Identifying why real earnings increase from the start of our time series to its end is beyond the scope of this paper.

[10]Readers should note that the random search models proposed by Lopes de Melo (2016), Hagedorn, Law, and Manovskii (2016) 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, can be helpful in assessing the robustness of our overall findings.

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).[11] This is a rough metric for how desirable a firm is to work for, which includes nonwage amenities.[12] To obtain something that is a similarly fast method for ranking workers, we use the faction of their careers that they spend in employment vs. nonemployment. We count workers who are more frequently employed as being more productive.[13] 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 and firms via revenue productivity, in the spirit of Bartolucci, Devicienti, and Monzón (2015) and Haltiwanger, Hyatt, and McEntarfer (2016). 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, Jarmin, Kulick, and Miranda (2015).[14] The labor productivity changes discontinuously after the year 2001, so using a crosswalk of firm in continuous operation from 2000 to 2002, we impute revenue productivity for the earlier years to smooth the discontinuity.

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 and labor market sorting, varies with the health of the labor market. We have several outcomes of interest: the share of workers and firms by type, the relative frequency of workers and firms of given types to be matched with each other (characterized by shares of worker-firm combinations), and the

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

[12] One 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).

[13] This 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 as much emphasis on nonemployment as a method of ranking workers as they do the use of the poaching hire share to rank firms, they do employ nonemployment duration as a method of ranking workers in Section 4.2.1 of their September 2016 draft.

[14] Our 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

worker flows into and from nonemployment and poaching flows across firms that determine (i.e., exhaustively 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.[15] 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.

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 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 0.5, while the poaching share and employment duration model produces the lowest correlation, at 0.21. The reranking and reservation wage method yields a somewhat higher degree of sorting than our additive worker and firm effects method, at 0.30 and 0.36, respectively.

[15]Note that the use of dummy variables to capture time effects substantially migtigates the time trends toward either the low or high tercile that would otherwise 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 it is these trend that are especially mitigated via the inclusion of time dummies.

3.2 Worker and Firm Composition

Panel 1(a) shows how the share of workers changes over time, focusing on how it changes in recessions.[16] Overall, the changes in the shares in these terciles are very small, with the share of workers moving up or down by less than 0.2 percentage points over the span of a quarter. A disproportionate amount of the movement occurs in the context of the two recessions, where the share of workers in the highest tercile increases, largely at the expense of the workers in the lowest tercile. This shift away from the lowest worker tercile toward the highest continues for the years following each of the recessions.[17] 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 exceeding 0.2 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.[18] Although the magnitude and statistical significance varies across the different methods, consistent patterns are evident (for example, the results using the revenue productivity are the smallest in magnitude and least often significant, but the signs are generally similar in magnitude to the other ranking methods). 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 an decrease in the share of workers in the lowest ranked tercile,

[16]Results are consistent when using the other ranking methods. See Appendix Figure C.1 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 C.2 to see the worker shares when ranking workers based on the share of their life-cycle they spend in nonemployment, and Appendix Figure C.3 for shares of the workforce when ranked by average firm-level revenue productivity.

[17]This 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.

[18]Similar specifications have been used to measure the cyclicality of job ladders in the labor market by, among others, Haltiwanger, Hyatt, and McEntarfer (2015).

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.[19] The worker changes in share are similar for the additive effects model and when workers are reranked following Hagedorn, Law, and Manovskii (2016). 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 that employment shifts away from higher productivity firms toward lower productivity firms.

3.3 Cyclical Labor Market Sorting

Now, we turn from composition to sorting. Figure 2 shows how worker sorting evolves over this time period.[20] 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 total employment, and so the share of low-ranked workers in all three firm categories sum to the share of low-ranked workers in Figure 1(a).[21] 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, later on in 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 more than offsets a slight decline in employment of low and middle type workers at low type firms at the outset of each of the two recessions.

Tables 3 and 4 quantifies how this sorting varies with the unemployment rate. Results are con-

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

[20] Again, we only show charts for our additive effects models. See Appendix Figures C.4, C.5, and C.6 for comparable figures from the other ranking methods.

[21] Note 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.

sistent 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.

3.4 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, which we now consider.[22] Figure 3(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, Hyatt, and McEntarfer (2015) 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. Figure 3(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 cyclicality is similar, with net nonemployment hiring falling sharply during the two recessions. Figure 3(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 moves a contributes to 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.

[22] Again, we only show charts for our additive effects models. See Appendix Figures C.7, C.8, and C.9 for comparable figures from the other ranking methods.

Table 5 quantifies how this varies 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 0.08 to 0.13 percentage point decrease (0.11 to 0.18 using the first difference of the unemployment rate) in the net hiring from nonemployment, and 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.

3.5 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.

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 we find no evidence of: 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 On-the-Job Search

In this section, we evaluate the ability of a rich model to fit the facts documented above.

We work with the model Lise and Robin (2016). 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. We briefly describe the main features here, see Lise and Robin (2016) 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. We assume that $f(x,y,z)$ is increasing in its first two arguments. This means that higher type workers are more productive workers, regardless of who they match with. A similar ranking holds for firms.

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. Then 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. Then production takes place and wages are paid.

A key feature of the Lise and Robin (2016) 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.[23]

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

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

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

[23] The exception is when the potential poaching firm cannot even offer enough to make on 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

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 (2016) 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 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. In particular, let $u_t(x)$ be the mass of unemployed type x workers at the start of period t. Let $h_t(x,y)$ be the mass of type x workers at type y jobs. The mass of type x workers is fixed at $l(x)$:

$$l(x) = u_t(x) + \int h_t(x,y)dy. \tag{2}$$

It will be convenient to define $u_{t+}(x)$ as unemployment after endogenous and exogenous separations:

$$u_{t+}(x) = u_t(x) + \int \left[\mathbf{1}\left\{S(x,y,z_t) < 0\right\} + \delta\mathbf{1}\left\{S(x,y,z_t) \geq 0\right\}\right] h_t(x,y)dy \tag{3}$$

and $h_{t+}(x,y)$ is employment after separations:

$$h_{t+}(x,y) = (1-\delta)\mathbf{1}\left\{S(x,y,z_t) \geq 0\right\} h_t(x,y). \tag{4}$$

During the meeting phase of a period, unemployed and employed workers enter the meeting function. Unemployed workers search with intensity 1, while employed workers search with intensity $s < 1$. Then the effective number of searching workers is

$$L_t = \int u_+(x)dx + s \int \int h_{t+}(x,y)dydx. \tag{5}$$

The meeting function is Cobb-Douglas:

$$m(L_t, V_t) = \alpha L_t^{0.5} V_t^{0.5} \tag{6}$$

where V_t is the total number of vacancies and $m(L_t, V_t)$ is the number of meetings that occur. Define $\lambda_t = \frac{m(L_t, V_t)}{L_t}$ as the rate at which an unemployed worker meets jobs. Since search is random, workers meet vacancies in proportion to their share of aggregate vacancies. We can write end of period unemployment as

$$u_{t+1}(x) = u_{t+}(x) \left[1 - \int \lambda_t \frac{v_t(y)}{V_t} \mathbf{1} \{ S(x,y,z_t) \geq 0 \} dy \right]. \tag{7}$$

Here $\lambda_t \frac{v_t(y)}{V_t}$ is the probability a worker meets a type y vacancy. If surplus is positive, the worker matches and exits unemployment. The integral is the probability an unemployed type x worker exits unemployment. The expression for end of period employment is more complex:

$$\begin{aligned} h_{t+1}(x,y) = h_{t+}(x,y) &\left[1 - \int s\lambda_t \frac{v_t(y')}{V_t} \mathbf{1} \left\{ S_t(x,y') > S_t(x,y) \right\} dy' \right] \\ &+ \int h_{t+}(x,y') s\lambda_t \frac{v_t(y)}{V_t} \mathbf{1} \left\{ S_t(x,y) > S_t(x,y') \right\} dy' \\ &+ u_{t+}(x) \lambda_t \frac{v_t(y)}{V_t} \mathbf{1} \{ S_t(x,y) \geq 0 \}. \end{aligned} \tag{8}$$

The first term is the mass of workers that are retained, failing to find a better firm to work for. The second term is the mass of workers that type y firms poach from other firms. The last term is the mass of hires from unemployment.

The equations above determine the evolution of unemployment and employment, given the surplus function and vacancies $v_t(y)$. The last remaining loose end is vacancy posting. This does depend on the full aggregate state, because even though the match surplus is independent of distributions, the firm's share of surplus is not. If most workers are unemployed, for example, the value of a vacancy will be high because the firm can exact more surplus than if most potential hires already had jobs and higher threat points. Let $J_t(t)$ be the value to the (type y) firm of meeting a worker. In equilibrium, the marginal vacancy cost will be equated with the expected benefits, implying

$$c'(v_t(y)) = q_t J_t(y)$$

In the calibration we follow Lise and Robin (2016) in setting

$$c(v) = c_0 \frac{1}{1+c_1} v^{1+c_1}$$

so the vacancy posting condition becomes

$$c_0 (v_t(y))^{c_1} = q_t J_t(y) \tag{9}$$

where $q_t = \frac{m(L_t, V_t)}{V_t}$ is the rate at which a vacancy meets workers. $J_t(y)$, in turn, is the sum of expected profits from poaching hires and expected profits from hiring the unemployed:

$$\begin{aligned} J_t(y) = & \int \frac{u_{t+}(x)}{L_t} \max\{S(x,y,z_t), 0\}\, dx \\ & + \int \int \frac{sh_+(x,y')}{L_t} \left[\max\left\{S(x,y,z_t) - S(x,y',z_t), 0\right\}\right] dxdy \end{aligned} \tag{10}$$

Here $\frac{u_{t+}(x)}{L_t}$ is the probability the vacancy meets an unemployed type x worker, conditional on meeting a worker. $\frac{sh_+(x,y')}{L_t}$ is the conditional probability that the worker is of type x and currently employed at a type y' firm.

Equations (1), (2), (3), (4), (5), (6), (7), (8), (9) and (10) define an equilibrium. The main endogenous quantities are $S(x,y,z_t)$, $h_t(x,y)$, $h_{t+}(x,y)$, $u_t(x)$, $u_{t+}(x)$, $v_t(y)$. See Lise and Robin (2016) for omitted details, the derivation of (1), and the specifics of the wage bargaining mechanism.

4.1 Estimation

Lise and Robin (2016) 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 (2016), roughly speaking, use duration dependence in unemployment to pin down worker type distribution, the cross-sectional dispersion of value added to pin down firm type dispersion, and time-series correlations in these objects to infer matching behavior.

In contrast, our data provides more direct measures of the joint match distribution. We can observe which workers match with which firms, and how that varies over the business cycle. In this section, we first construct the LEHD moments reported above within the Lise and Robin (2016) model. We discuss how the model-implied moments differ from the those in the data. Then we add the LEHD moments as additional targets for the SMM estimation, and discuss the ability of the model to jointly match all the moments.

4.1.1 Construction of worker and firm shares

In this paper, we focus on the third ranking schema, nonemployment duration and poaching share. In future work we plan to add the other ranking methods. 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 (2016) model all workers of a given type have the same expected unemployment duration, and all firms of a given type have the same 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.[24]

Given a parameter guess, we order worker types by their expected unemployment duration. We

[24]Obviously, 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.

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 4. These moments are targeted in addition to the 28 moments Lise and Robin (2016) 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 & Robin. The production function has 6 free parameters:

$$p(x,y,z) = z(p_1 + p_2x + p_3y + p_4x^2 + p_5y^2 + p_6xy) \tag{11}$$

The aggregate meeting function is Cobb-Douglas with elasticity 0.5 and efficiency α, to be estimated. The convex vacancy posting cost function is $(1+c_1)^{-1}c_0v^{1+c_1}$, 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 it's 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 & Robin. There are some obvious differences. For example, the intensity of on the job search, s, is about half what Lise and Robin (2016) estimate. The rate of exogenous job destruction δ is higher than in their model. Finally, the convexity of vacancy posting costs c_1 is significantly higher in our model. Taken by itself, this will tend to make recruiting less responsive to productivity shocks.

Table 8 shows the LEHD moments.[25] Each β the coefficient from a regression of the worker tercile-firm tercile share of employment on the first difference of unemployment. For example, β_{LH} is the coefficient for matches between low type workers and high type firms. The first column is

[25] Note that the targeted moments (first column) are slightly different from those reported in the previous section. The model is targeting an older set moments, though they are qualitatively very close to the more recent estimates.

essentially column 3 of Table 3. The second column is the same quantities, calculated from simulated data using the from Lise and Robin (2016). 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.[26] Second, in the estimation in Lise and Robin (2016), low type firms *decrease* in match share during recessions, while high type firms *increase*. This can be seen by summing up $\beta_{LL}+\beta_{ML}+\beta_{HL}$ and $\beta_{LH}+\beta_{MH}+\beta_{HH}$ respectively. Thus, the Lise & Robin economy fails to match the stylized fact that firm type distribution shifts down in recessions. 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 "sullying" 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 (2016) targeted moments (which we also target). Here, we see that our ability to fit the LEHD moments comes at a significant cost. Perhaps most troublingly, $\text{corr}[V,U]$ is close to zero, meaning that while the Beviridge curve relationship is very noisy. In contrast, $\text{corr}[V,U]$ is below -0.8 both in the data and in the Lise and Robin (2016) estimation. Another contrast is that in our estimation vacancies are nearly uncorrelated with value added.

Figure 4 shows the acceptance sets, both for the Lise and Robin (2016) model economy and ours. The solid lines are boundaries of the acceptance sets for various values of the aggregate shock. The dotted line marks each worker's most preferred firm type. The top panel is identical to Figure 4 of Lise and Robin (2016), with the exception that the agent type distributions have been normalized to a uniform distribution. Recall that the both the worker type distribution and the production function are being estimated. In fact, any economy with any worker type distribution is isomorphic to an economy with a uniform worker distribution and a properly rescaled production function. Similarly, firm types can be made *approximately* uniform by "renaming" each firm type. Normalizing the firm type distribution is complicated by the fact that the distribution of job types is time-varying. We normalize so that the time-averaged job type distribution is uniform. This facilitates comparison between different economies, as any two regions with the same area on the graph cover (approximately) the same number of agents. If the distributions are left unnormalized then large area (say, worker types 0.8-1) may cover only a tiny fraction of the population, but a small region (say, worker types 0.1-0.12) may cover

[26] Though the attenuation bias noted above may play a role here.

many more agents.

Figure 4 shows that the acceptance sets are qualitatively similar, with increasing boundaries and increasing "most-preferred" firm types. The solid acceptance set boundaries are more vertical in the LEHD moment estimation. This indicates that in recessions the job losses are a function of worker type mostly, not firm type. This is consistent with the reasoning outlined in the introduction: If worker productivity is the primary determinant of the productivity of a match, 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. By the same token, the distribution of firm types is not sensitive to the cleansing effects of recessions. In the absence of cleansing, low type firms benefit from the lack of poaching in a recession. Thus, low type firms accumulate a relatively larger share of workers in recessions, as observed.

To summarize, the Lise and Robin (2016) economy is qualitatively similar to ours along a number of dimensions. However, the requiring the economy to match the LEHD moments appears to severely limit it's ability to match other moments, including the Beveridge curve. Adding the LEHD moments forces most of the cyclical variation in acceptance sets to occur along the worker dimension. This means that low type workers are the marginal matches, leaving low type firms to benefit from the lack of poaching in a downturn.

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 nonemplpoyment, 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 calibrated a model that can generate these properties. To do so, we employed the Lise and Robin (2016) framework, replicating their complete estimation with the addition of the moments calculated from the LEHD. The estimated production function and acceptance sets are qualitatively similar to Lise and Robin (2016), although our estimated model has a weak Beveridge curve. Our acceptance sets vary mostly along the worker dimension over the cycle, generating cleansing on the worker side, and allowing low type firms to accumulate workers during downturns through a lack of poaching.

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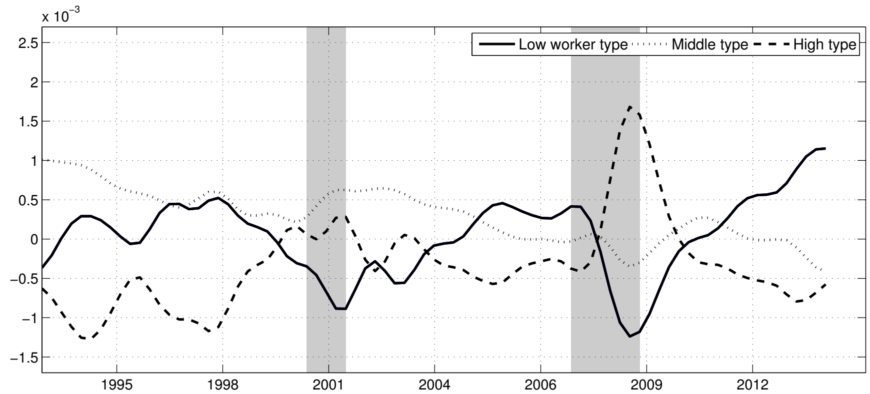
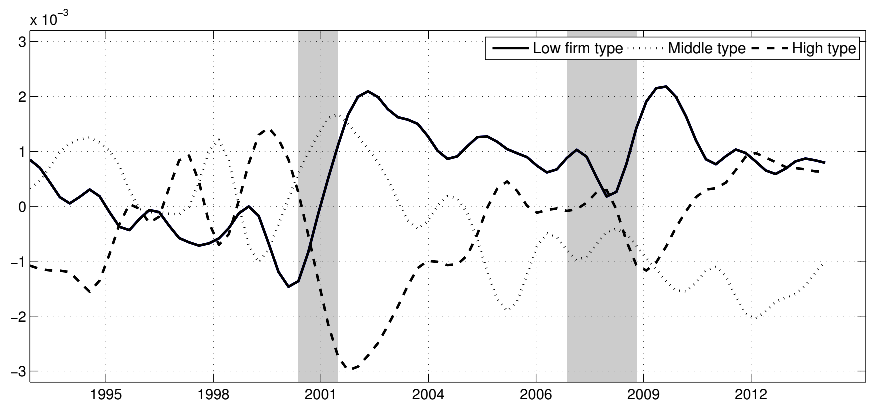
Tables and Figures

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

(a) Workers



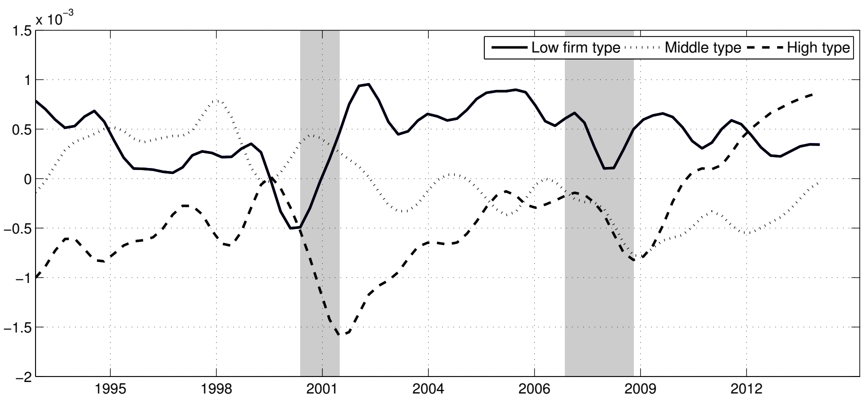
(b) Firms



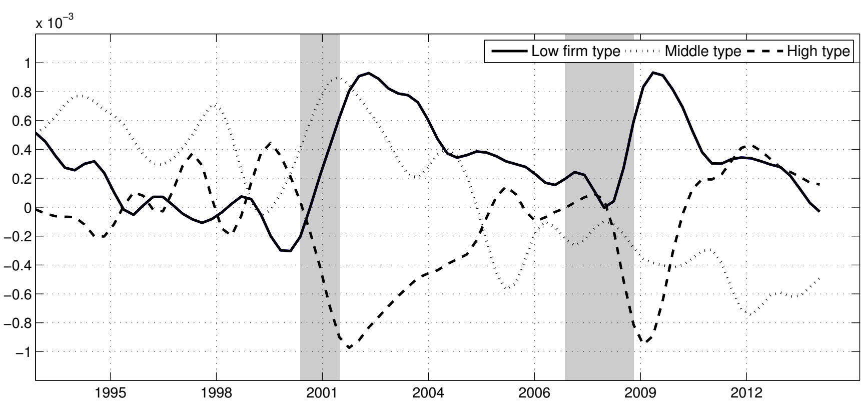
Notes: Productivity terciles calculated off of additive worker and firm effects model.

Figure 2: Change in Worker and Firm Share Combinatons by Productivity Tercile (Additive Model)

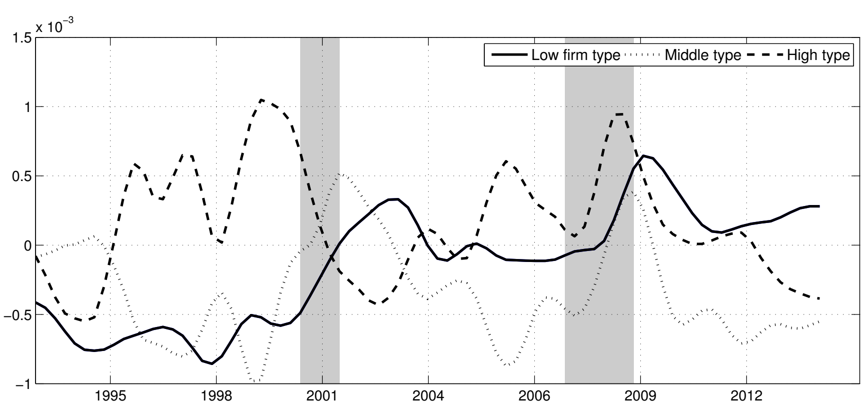
(a) Workers: Low



(b) Workers: Middle



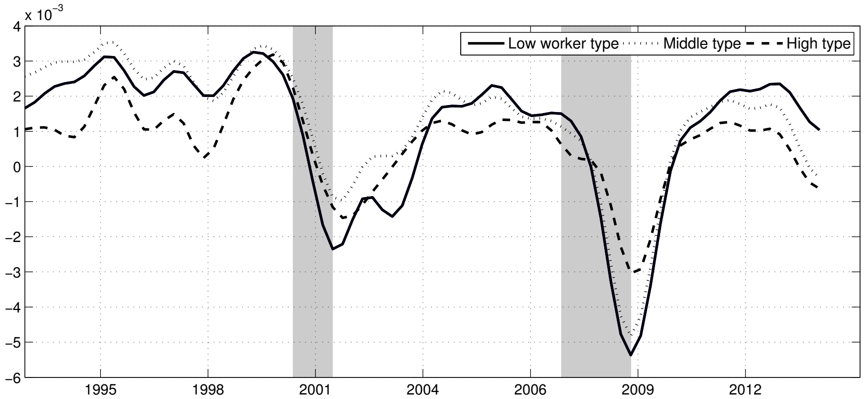
(c) Workers: High



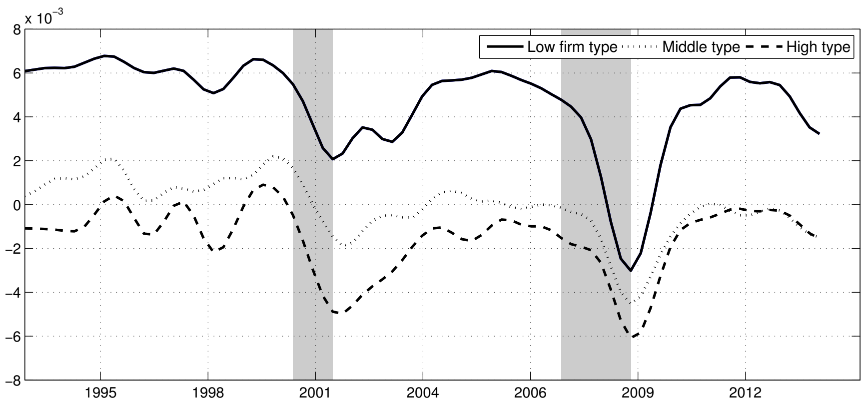
Notes: Productivity terciles calculated off of additive worker and firm effects model.

Figure 3: Net Change in Employment via Nonemployment and Poaching (Additive Model)

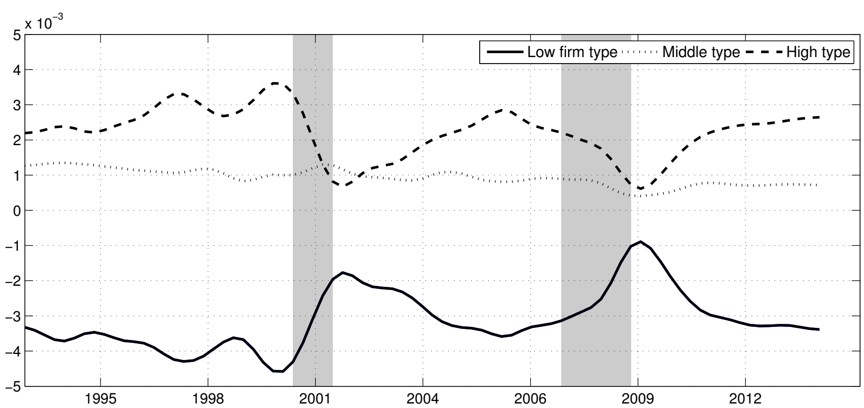
(a) Workers: Nonemployment



(b) Firms: Nonemployment



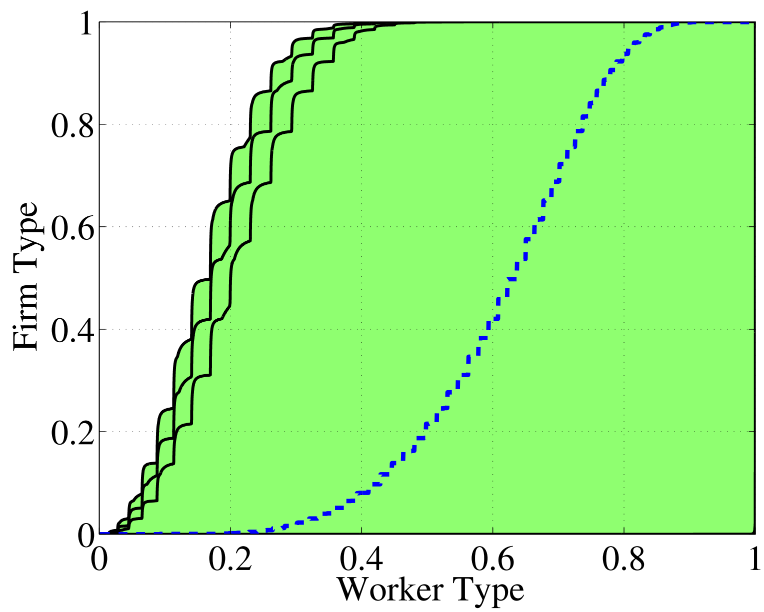
(c) Firms: Poaching



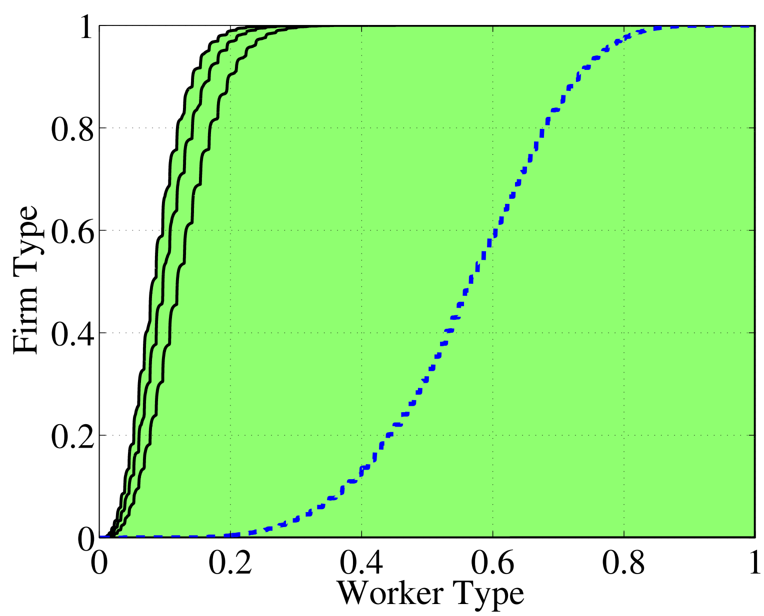
Notes: Productivity terciles calculated off of additive worker and firm effects model.

Figure 4: Model Implied Acceptance Sets

(a) Lise & Robin Estimation



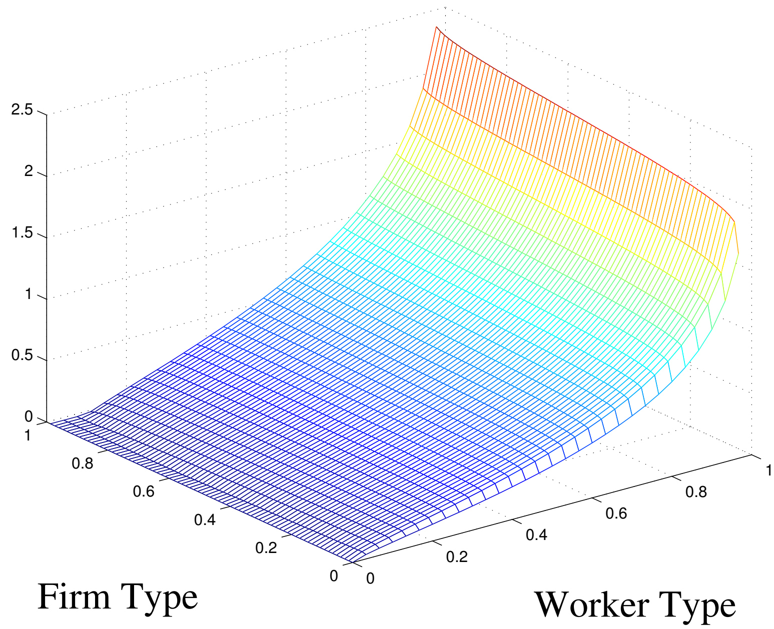
(b) LEHD Moment Estimation



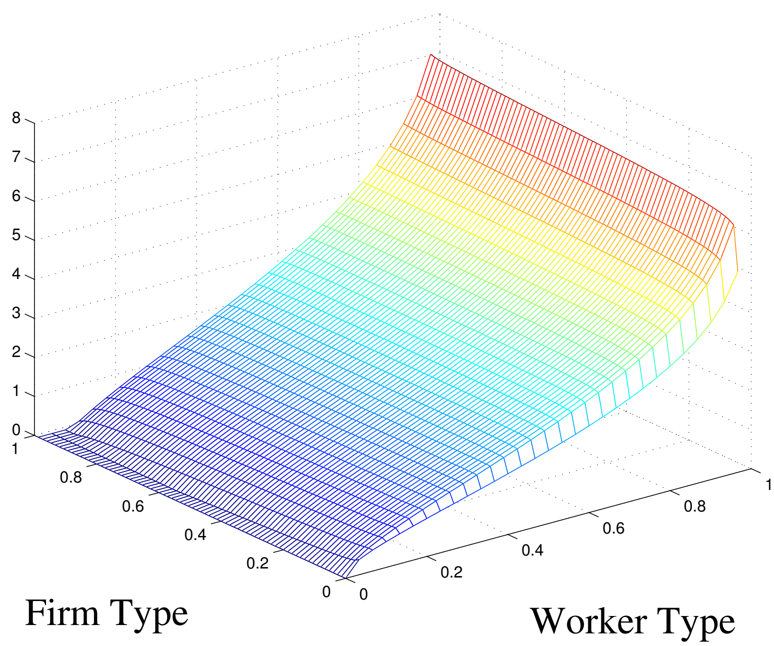
Notes: Worker type distribution normalized to a uniform distribution. The firm type distribution is normalized so that the time-averaged job distribution is uniform as well. Solid lines are the bounders of acceptance sets at the 90th, 50th and 10th percentile of the aggregate productivity distribution. Dotted line is the worker's maximal firm type. The "scalloping" in the top panel is the result of smoothing the discretized worker and firm type grids.

Figure 5: Model Implied Production Functions

(a) Lise & Robin Estimation



(b) LEHD Moment Estimation



Notes:Worker type distribution normalized to a uniform distribution.

Table 1: Correlation of Worker and Firm Ranks Across Models

	Firm Rankings				Worker Rankings			
	Additive Worker-Firm	**Reranking**	**Poaching Share**	**Revenue Productivity**	**Additive Worker-Firm**	**Reranking**	**Employment**	**Revenue Productivity**
				Firm Rankings				
Addititve	1.00	0.63	0.43	0.32	0.30	0.29	0.17	0.20
Reranking	0.63	1.00	0.35	0.31	0.45	0.36	0.16	0.22
Poaching Share	0.43	0.35	1.00	0.19	0.20	0.19	0.21	0.12
Productivity	0.32	0.31	0.19	1.00	0.21	0.19	0.07	0.55
				Worker Rankings				
Additive	0.30	0.45	0.20	0.21	1.00	0.90	0.27	0.19
Reranking	0.29	0.36	0.19	0.19	0.90	1.00	0.24	0.17
Employment	0.17	0.16	0.21	0.07	0.27	0.24	1.00	0.01
Productivity	0.20	0.22	0.12	0.55	0.19	0.17	0.01	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**
		Difference in Unemployment from HP Trend		
Workers: Low	-3.17**	-2.78**	-12.10***	-0.85
	(1.20)	(1.07)	(3.09)	(1.06)
Workers: High	2.37**	2.06**	8.21***	0.52
	(1.10)	(1.03)	(2.24)	(0.81)
Firms: Low	5.52***	5.32***	2.81	1.06
	(1.45)	(1.51)	(2.63)	(1.81)
Firms: High	-6.55***	-5.06***	-5.21***	-0.20
	(1.79)	(1.46)	(1.81)	(1.62)
		First-Difference of Unemployment Rate		
Workers: Low	-3.84***	-3.24***	-15.70***	-0.31
	(0.81)	(0.73)	(1.70)	(0.78)
Workers: High	4.41***	3.59***	11.44***	1.31**
	(0.65)	(0.65)	(1.20)	(0.58)
Firms: Low	2.90**	2.38**	4.92***	1.18
	(1.11)	(1.16)	(1.86)	(1.32)
Firms: High	-4.77***	-4.08***	-4.79***	-1.07
	(1.31)	(1.05)	(1.28)	(1.18)

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 Share and Unemployment (HP)

	Additive Worker and Firm Effects	**Rerank Workers Plus Reservation**	**Poaching Share and Nonemp.**	**Revenue Productivity**
		Employed at Low-Type Firms		
Workers: Low	0.89	0.90	-3.45**	-0.34
	(0.95)	(1.02)	(1.55)	(1.48)
Workers: Medium	2.66***	2.66***	3.99***	1.17*
	(0.53)	(0.62)	(1.22)	(0.63)
Workers: High	1.98***	1.76***	2.26**	0.23
	(0.49)	(0.53)	(1.02)	(0.44)
		Employed at Medium-Type Firms		
Workers: Low	-1.37**	-1.49**	-3.04**	-0.19
	(0.54)	(0.60)	(1.43)	(0.56)
Workers: Medium	0.81	0.15	1.99***	-0.26
	(0.56)	(0.60)	(0.71)	(0.69)
Workers: High	1.59**	1.08	3.45***	-0.41
	(0.74)	(0.74)	(0.90)	(0.51)
		Employed at High-Type Firms		
Workers: Low	-2.69***	-2.19***	-5.58***	-0.32
	(0.71)	(0.63)	(1.32)	(0.67)
Workers: Medium	-2.66***	-2.09***	-2.12***	-0.59
	(0.63)	(0.60)	(0.71)	(0.81)
Workers: High	-1.20	-0.78	2.50***	0.70
	(0.97)	(0.73)	(0.87)	(0.92)

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 (FD)

	Additive Worker and Firm Effects	**Rerank Workers Plus Reservation**	**Poaching Share and Nonemp.**	**Revenue Productivity**
		Employed at Low-Type Firms		
Workers: Low	0.43	0.68	-2.44**	1.65
	(0.70)	(0.75)	(1.14)	(1.07)
Workers: Medium	1.16***	0.91*	4.03***	0.41
	(0.43)	(0.50)	(0.84)	(0.47)
Workers: High	1.31***	0.80*	3.33***	-0.88***
	(0.36)	(0.41)	(0.67)	(0.31)
		Employed at Medium-Type Firms		
Workers: Low	-0.99**	-1.18***	-6.30***	-0.97**
	(0.40)	(0.44)	(0.79)	(0.39)
Workers: Medium	0.72*	1.02**	1.95***	0.72
	(0.41)	(0.43)	(0.50)	(0.50)
Workers: High	2.15***	1.86***	4.23***	0.15
	(0.50)	(0.50)	(0.54)	(0.38)
		Employed at High-Type Firms		
Workers: Low	-3.28***	-2.74***	-6.91***	-0.98**
	(0.42)	(0.38)	(0.72)	(0.48)
Workers: Medium	-2.45***	-2.27***	-1.76***	-2.13***
	(0.43)	(0.39)	(0.51)	(0.54)
Workers: High	0.95	0.93*	3.88***	2.04***
	(0.71)	(0.53)	(0.50)	(0.63)

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 Net Hiring and Unemployment

	Additive Worker and Firm Effects	**Rerank Workers Plus Reservation**	**Poaching Share and Nonemp.**	**Revenue Productivity**
		Difference in Unemployment from HP Trend		
Workers: Low	-13.85***	-13.11***	-22.69***	-10.86***
Nonemployment	(2.87)	(2.79)	(5.13)	(2.55)
Workers: High	-7.96***	-8.42***	-1.88	-9.76***
Nonemployment	(2.43)	(2.40)	(1.59)	(2.40)
Firms: Low	-11.85***	-10.99***	-12.58***	-12.60***
Nonemployment	(3.15)	(3.06)	(3.27)	(3.17)
Firms: High	-10.93***	-10.23***	-9.12***	-8.78***
Nonemployment	(2.80)	(2.58)	(2.03)	(2.26)
Firms: Low	6.82***	5.54***	5.05***	3.60***
Poaching	(0.96)	(1.00)	(1.08)	(0.87)
Firms: High	-6.20***	-5.35***	-6.35***	-2.55***
Poaching	(0.94)	(0.93)	(1.02)	(0.88)
		First-Difference of Unemployment Rate		
Workers: Low	-17.62***	-16.75***	-29.64***	-13.24***
Nonemployment	(1.29)	(1.29)	(2.47)	(1.42)
Workers: High	-9.05***	-9.64***	-1.55	-11.9***
Nonemployment	(1.59)	(1.54)	(1.16)	(1.37)
Firms: Low	-17.43***	-17.33***	-15.89***	-15.67***
Nonemployment	(1.51)	(1.38)	(1.87)	(1.80)
Firms: High	-13.34***	-11.97***	-11.35***	-11.58***
Nonemployment	(1.64)	(1.55)	(1.05)	(1.23)
Firms: Low	6.07***	5.53***	6.21***	3.02***
Poaching	(0.58)	(0.59)	(0.54)	(0.62)
Firms: High	-5.35***	-4.91***	-6.07***	-2.58***
	(0.61)	(0.59)	(0.60)	(0.61)

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**
	Difference in Unemployment from HP Trend			
Unemployment (HP)	0.04	0.14	0.28**	0.38*
	(0.25)	(0.14)	(0.13)	(0.22)
	First-Difference of Unemployment			
Unemployment (FD)	0.76***	0.44***	0.38***	0.70***
	(0.16)	(0.09)	(0.09)	(0.14)

Notes: Dependent Variable: Correlation of Worker and Firm Ranks within given model for each quarter. Regression of these correlations for each quarter on the seasonlly-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 Estimates**	**LEHD Moments Estimates**
α	0.497	0.769
s	0.027	0.010
c_0	0.028	0.028
c_1	0.084	0.213
δ	0.013	0.029
σ	0.071	0.074
ρ	0.9997	0.9997
β_1	2.148	3.300
β_2	12.001	6.021
p_1	0.003	0.001
p_2	2.053	2.745
p_3	-0.140	-0.230
p_4	8.035	8.102
p_5	-1.907	-1.940
p_6	6.596	6.577

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

Moment	**Data**	**Lise & Robin Estimation**	**LEHD Moments Estimation**
β_{LL}	-1.900	-343.294	3.086
β_{ML}	4.453	51.521	15.500
β_{HL}	4.523	-49.866	5.210
β_{LM}	-7.211	-35.390	-9.241
β_{MM}	2.599	-37.221	-1.814
β_{HM}	4.668	404.378	4.322
β_{LH}	-9.180	-165.962	-9.258
β_{MH}	-1.876	258.472	-5.981
β_{HH}	3.924	-82.638	-1.824

Notes: Coefficient β_{ij} is the impact of a 1 percent change in the unemployment rate on the share of matches between type i workers and type j firms, where i and j can be low (L), medium (M), or high (H)

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

Moment	Data	Lise & Robin Estimation	LEHD Moments Estimation
$\mathbb{E}[U]$	0.058	0.059	0.060
$\mathbb{E}[U^{5p}]$	0.035	0.032	0.038
$\mathbb{E}[U^{15p}]$	0.018	0.018	0.032
$\mathbb{E}[U^{27p}]$	0.010	0.011	0.029
$\mathbb{E}[UE]$	0.421	0.468	0.357
$\mathbb{E}[EU]$	0.025	0.028	0.023
$\mathbb{E}[EE]$	0.025	0.025	0.086
$\mathbb{E}[V/U]$	0.634	0.744	1.341
$\mathbb{E}[\text{sd labor prod}]$	0.494	0.505	0.189
$\text{sd}[V]$	0.206	0.105	0.126
$\text{sd}[VA]$	0.033	0.034	0.042
$\text{autocorr}[VA]$	0.932	0.991	0.993
$\text{corr}[V,U]$	-0.846	-0.975	-0.067
$\text{corr}[U,VA]$	-0.860	-0.983	-0.977
$\text{sd}[U]$	0.191	0.203	0.275
$\text{sd}[U^{5p}]$	0.281	0.315	0.243
$\text{sd}[U^{15p}]$	0.395	0.413	0.240
$\text{sd}[U^{27p}]$	0.478	0.439	0.266
$\text{sd}[UE]$	0.127	0.127	0.093
$\text{sd}[EU]$	0.100	0.095	0.350
$\text{sd}[EE]$	0.095	0.112	0.670
$\text{sd}[V/U]$	0.381	0.306	0.309
$\text{sd}[\text{sd labor prod}]$	0.039	0.038	0.015
$\text{corr}[V,VA]$	0.721	0.996	0.032
$\text{corr}[UE,VA]$	0.878	0.978	-0.435
$\text{corr}[EU,VA]$	-0.716	-0.910	-0.975
$\text{corr}[UE,EE]$	0.695	0.977	-0.858
$\text{corr}[\text{st labor prod},VA]$	-0.366	-0.361	-0.499

Appendices

A Employment and Transition Definitions

We use 11 states of LEHD microdata that have data available for 1994-2014.[27] 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 traisitions 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:

[27]Note 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 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 $\xi_c t$ 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 $\widehat{\theta_i}$ of the worker effect. We then proceed as follows.

1. Estimate the intial firm effects $\widehat{\psi_j} = w_{ijt} - \widehat{\theta_i}$.
2. Estimate the birth cohort by time effects $\widehat{\xi_{ct}} = w_{ijt} - \widehat{\theta_i} - \widehat{\psi_j}$,
3. Update the worker effects $\widehat{\theta_i} = w_{ijt} - \widehat{\psi_j} - \widehat{\xi_{ct}}$.
4. Update the worker effects $\widehat{\psi_j} = w_{ijt} - \widehat{\theta_i} - \widehat{\xi_{ct}}$.
5. Proceed back to step 2 unless a goodness-of-fit criterion is reached.

We then group each of the employment-weighted firm effects $\widehat{\psi_j}$, and the participation-weighted worker effects $\widehat{\theta_i}$ into terciles.

B.2 Worker Reranking

We implement an algorithm is a simple method of ranking workers and firms that borrows heavily from Hagedorn, Law, and Manovskii (2016) (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 $Var(\varepsilon_t) = \sigma^2$ 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: $\tau_0^2 \to \infty$. 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

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

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 $\{1,2,..N\}$) of the worker i.

2. Starting from a ranking $\hat{\Pi}_n$ choose a random worker name i from $\{1,2,..N\}$ and a random worker rank r from $\{1,2,..N\}$.

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 HLM Firm Ranking - NE

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 HLM ID Noise Algorithm.

IDNoise Algorithm To address noise in the classification of workers' types, HLM 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. HLM assign these workers with noisy worker types to a set $\hat{N}$. For each firm j, the IDNoise algorithm identifies $\hat{B}(\hat{x}, j)$, 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 nonemployement 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:

$$\pi(\hat{x}, j) = \frac{u(\hat{x}) 1 \left[p(\hat{x}, j) > 0\right]}{\sum_{\hat{x}} u(\hat{x}) 1 \left[p(\hat{x}, j) > 0\right]} \tag{12}$$

   - $F\left(p(\hat{x}, j), \pi(\hat{x}, j), N(j)\right)$: 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, $F\left(p(\hat{x}, j), \pi(\hat{x}, j), N(j)\right)$ is:

$$F\left(p(\hat{x}, j), \pi(\hat{x}, j), N(j)\right) = \sum_{i=0}^{p(\hat{x}, j)} \begin{pmatrix} N(j) \\ i \end{pmatrix} \pi(\hat{x}, j)^{i} \left(1 - \pi(\hat{x}, j)\right)^{N(j)-i} \tag{13}$$

2. For each worker type $\hat{x}$, initialize $\hat{B}(\hat{x}, j) = 1$ if the firm hires any workers of that estimated type ($p(\hat{x}, j) > 0$)

3. * for all worker types, $\hat{x}$, with $\hat{B}(\hat{x}, j) = 1$

   - If the worker type, $\hat{x}$, is the lowest (=1) or highest (=50) worker types and $F\left(p(\hat{x}, j), \pi(\hat{x}, j), N(j)\right) \leq 0.1$, then set $\hat{B}(\hat{x}, j) = 0$ and return to *.
   - For all other worker types, if either $\hat{B}(\hat{x}-1, j) = 0$ or $\hat{B}(\hat{x}+1, j) = 0$ and $F\left(p(\hat{x}, j), \pi(\hat{x}, j), N(j)\right) \leq 0.1$, then set $\hat{B}(\hat{x}, j) = 0$ and return to *.

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

Identifying the Reservation Wage of Each Worker Type When determining the reservation wages of each worker type, we follow HLM in excluding the earnings histories of any worker i with a noisy worker type ($i \in \hat{N}$). 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 HLM 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 HLM, 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:

$$\Omega^u(j) = \sum_{\hat{x} \text{ s.t. } \hat{B}(\hat{x}, j)=1} \frac{\frac{u(\hat{x})}{U}\left(\bar{w}(\hat{x}, j) - w^r(\hat{x})\right)}{\sum_{\hat{x} \text{ s.t. } \hat{B}(\hat{x}, j)=1} \frac{u(\hat{x})}{U}} \tag{14}$$

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:

$$\tilde{q}^u(j) = \sum_{\hat{x} \text{ s.t. } \hat{B}(\hat{x}, j)=1} \frac{u(\hat{x})}{U} \tag{15}$$

B.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 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.[28] 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 availalble, with priority given to the latter. These data are Windsorized 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. (2014).

[28] Recent work by Haltiwanger et al. (2015) 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.

B.4.1 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.

B.4.2 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 avai;alble 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

$$lp_n = \begin{array}{l} \beta_0^b + \beta_1^b * lp_o + \beta_2^b * lp_o^2 + \beta_3^b * firmsize + \beta_4^1 * firmage + \\ \beta_5^b * firmsize * firmage + \beta_6^b * firmsize^2 + \beta_7^b * firmage^2 \end{array}$$

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

B.4.3 Ranking Workers and Firms

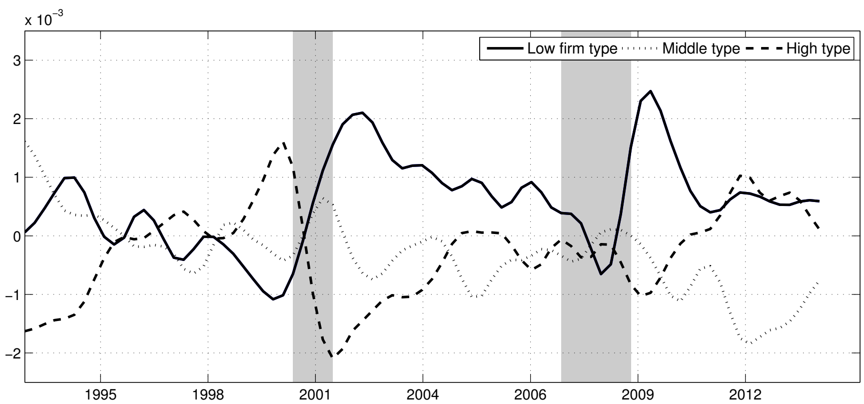
Having attached revenue to all firms in the LEHD data, we proceed in a simple manner to produce ranks of workers and firms based on revenue. We rank firms based on the residual firm productivity from year of entry by quarter dummy variable regression. We rank workers based on the residual firm productivity from year of birth by quarter dummy variable regression.

C Supplemental Tables Figures

Figure C.1: Change in Worker and Firm Shares, by Productivity Tercile (Reranking)

(a) Workers

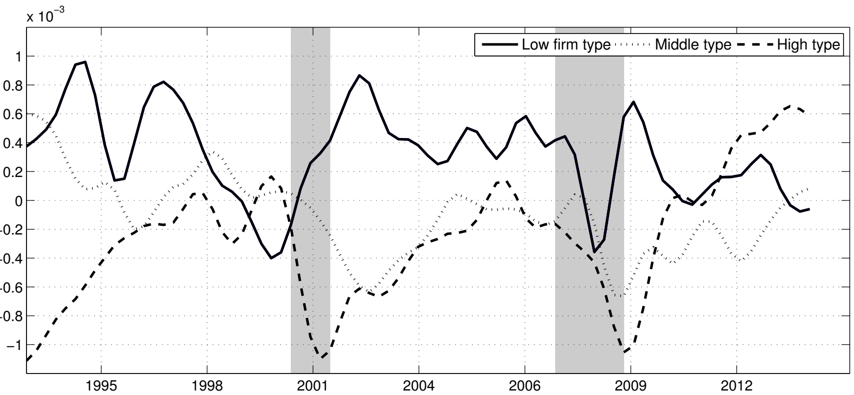
(b) Firms



Notes: Productivity terciles calculated off of worker reranking model.

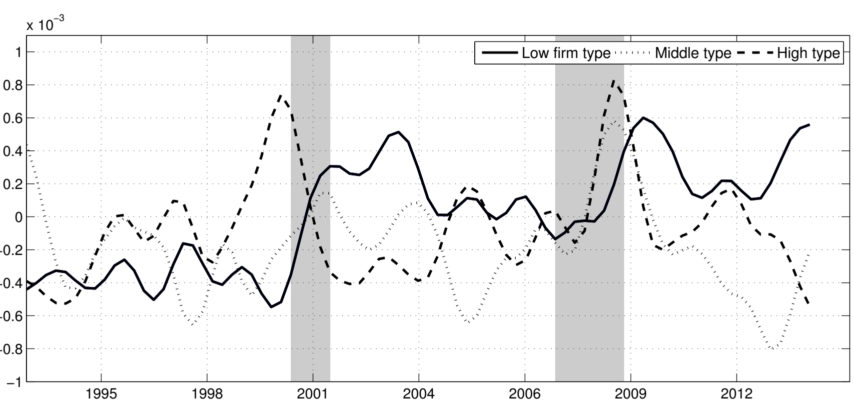
Figure C.2: Change in Worker and Firm Combinaton Shares, by Productivity Tercile (Reranking)

(a) Workers: Low



(b) Workers: Middle

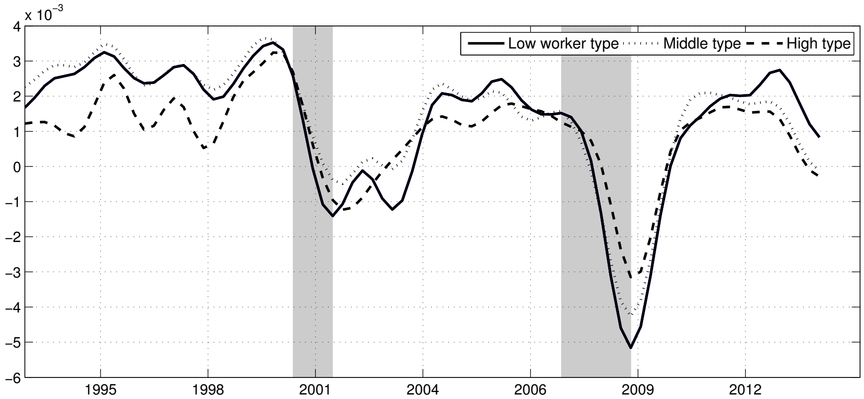
(c) Workers: High



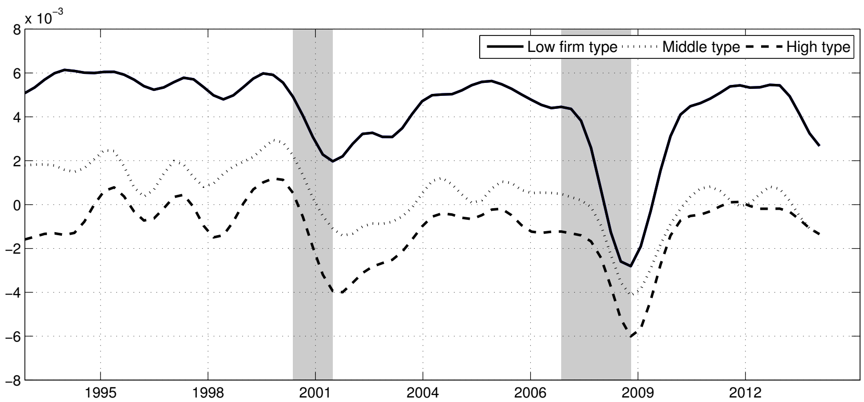
Notes: Productivity terciles calculated off of worker reranking model.

Figure C.3: Net Change in Employment via Nonemployment and Poaching (Reranking)

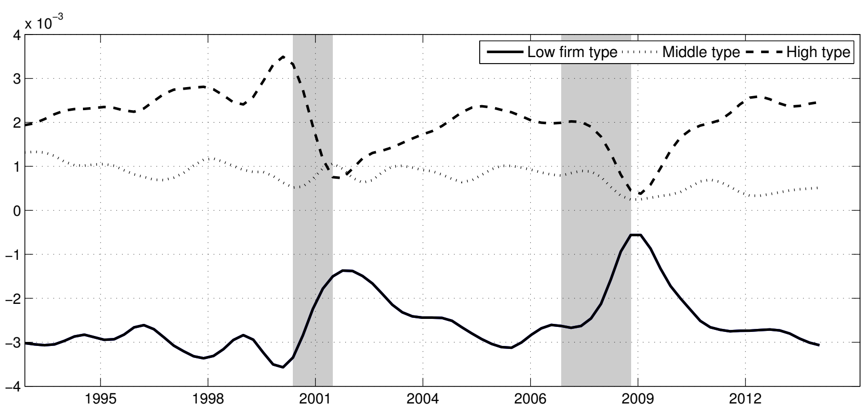
(a) Workers: Nonemployment



(b) Firms: Nonemployment



(c) Firms: Poaching

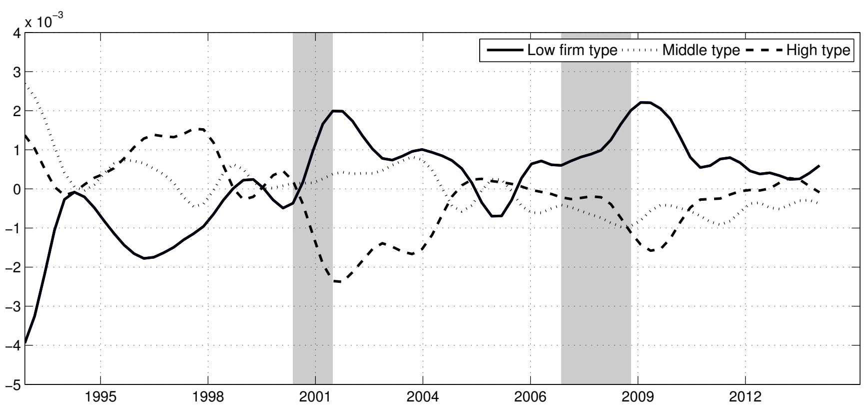


Notes: Productivity terciles calculated off of worker reranking model.

Figure C.4: Change in Worker and Firm Shares, by Productivity Tercile (Poaching Hire and Nonemp.)

(a) Workers

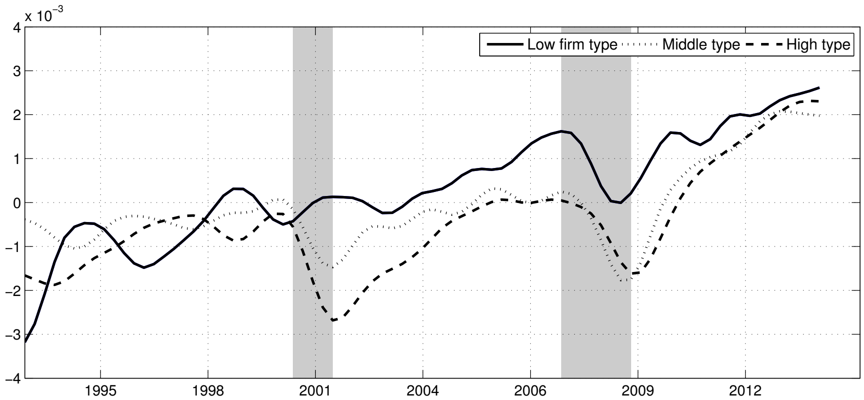
(b) Firms



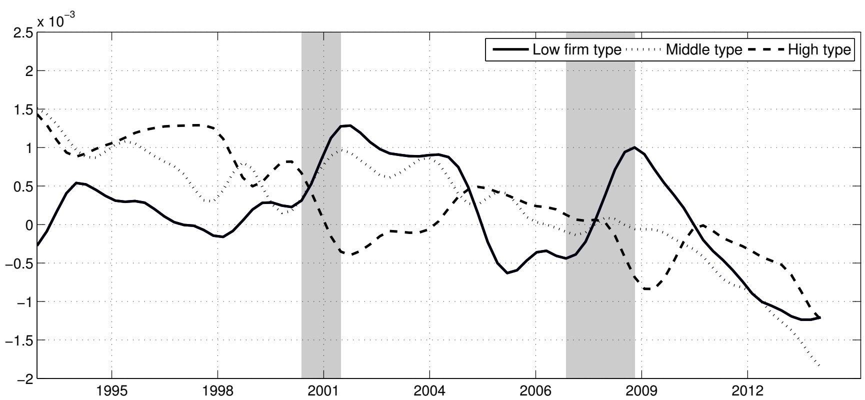
Notes: Productivity terciles calculated off of nonemployment and poaching hire share model.

Figure C.5: Change in Worker and Firm Combination Shares, by Productivity Tercile (Poaching Hire and Nonemp.)

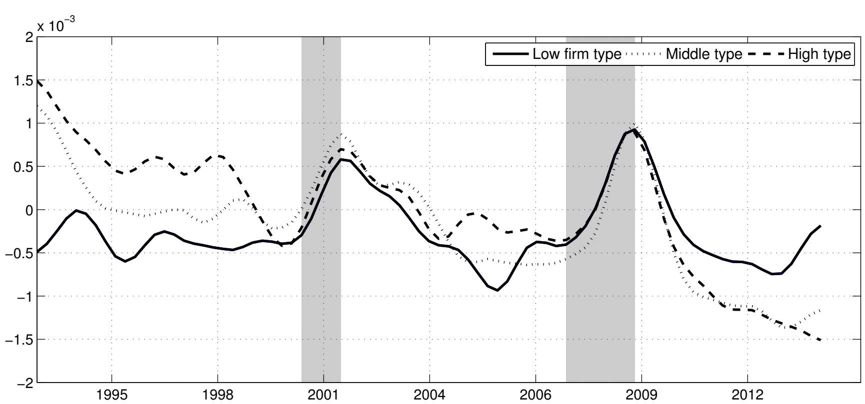
(a) Workers: Low



(b) Workers: Middle



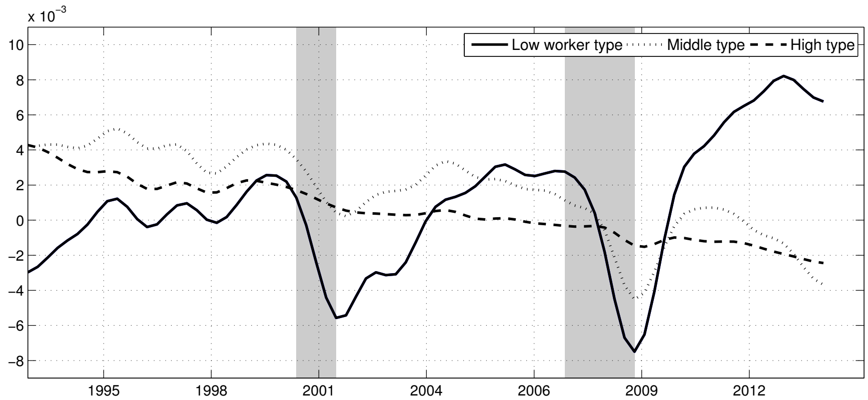
(c) Workers: High



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

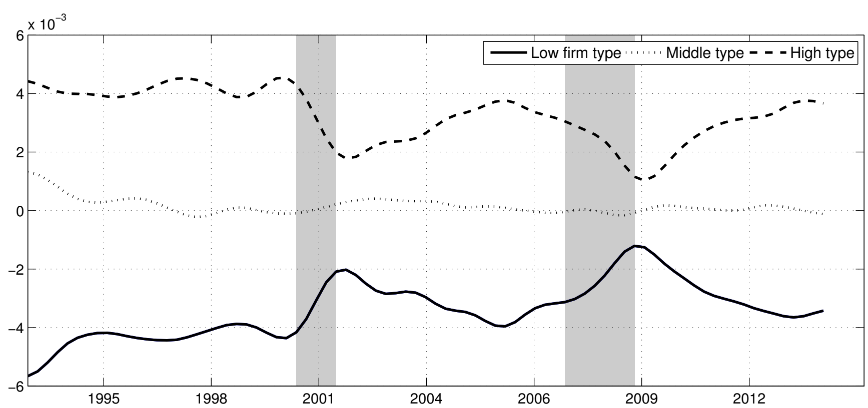
Figure C.6: Net Change in Employment via Nonemployment and Poaching (Poaching Hire and Nonemp.)

(a) Workers: Nonemployment



(b) Firms: Nonemployment

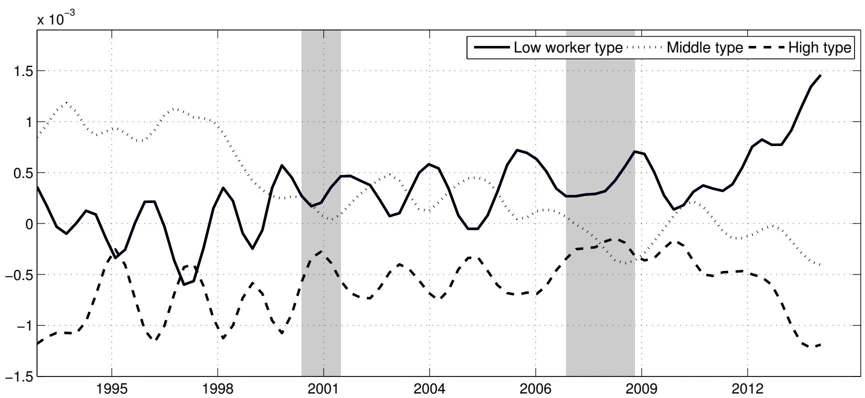
(c) Firms: Poaching



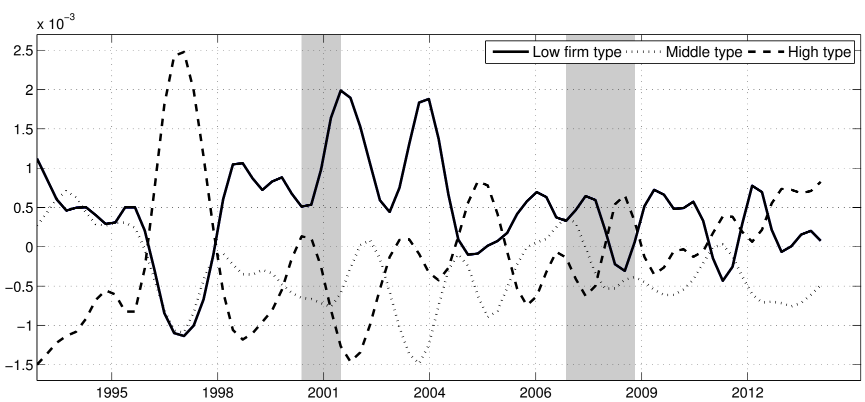
Notes: Productivity terciles calculated off of nonemployment and poaching hire share model.

Figure C.7: Change in Worker and Firm Share, by Productivity Tercile (Revenue Productivity)

(a) Workers



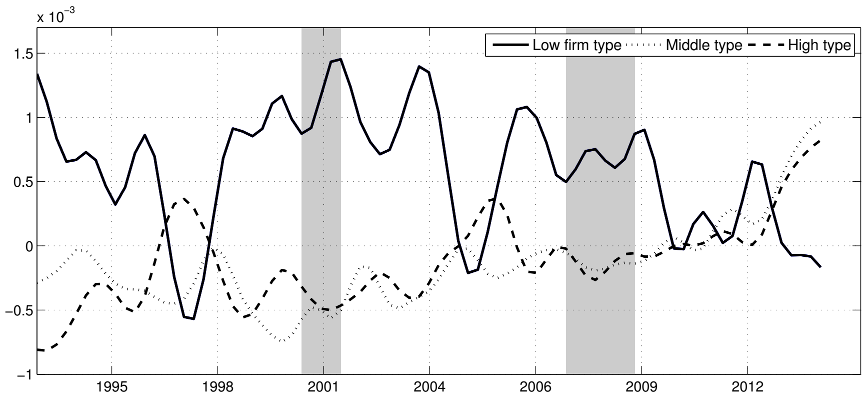
(b) Firms



Notes: Productivity terciles calculated off of average revenue productivity.

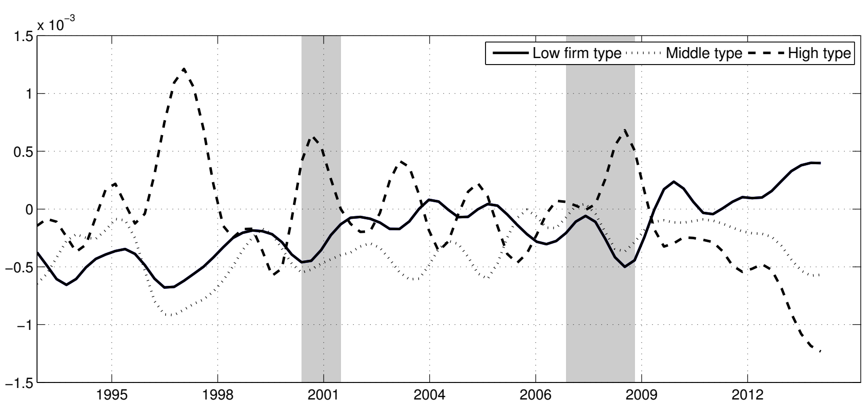
Figure C.8: Change in Worker and Firm Share Combinatons, by Productivity Tercile (Revenue Productivity)

(a) Workers: Low



(b) Workers: Middle

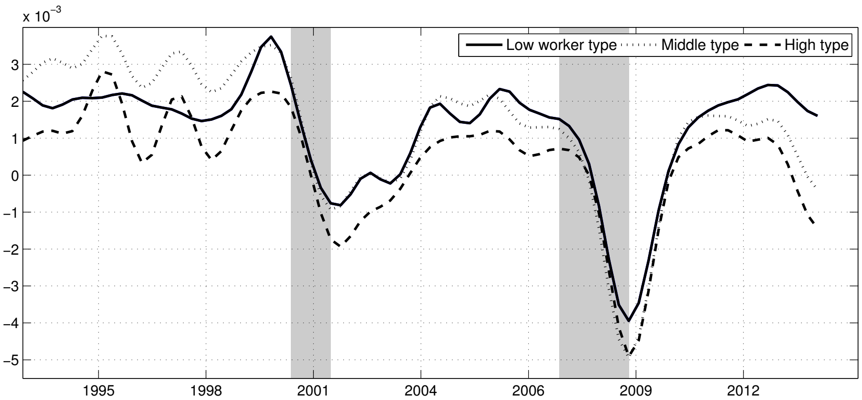
(c) Workers: High



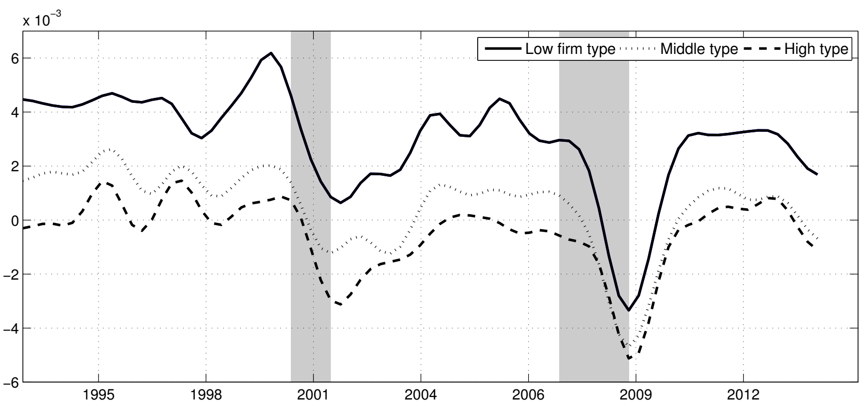
Notes: Productivity terciles calculated off of average revenue productivity.

Figure C.9: Net Change in Employment via Nonemployment and Poaching (Revenue Productivity)

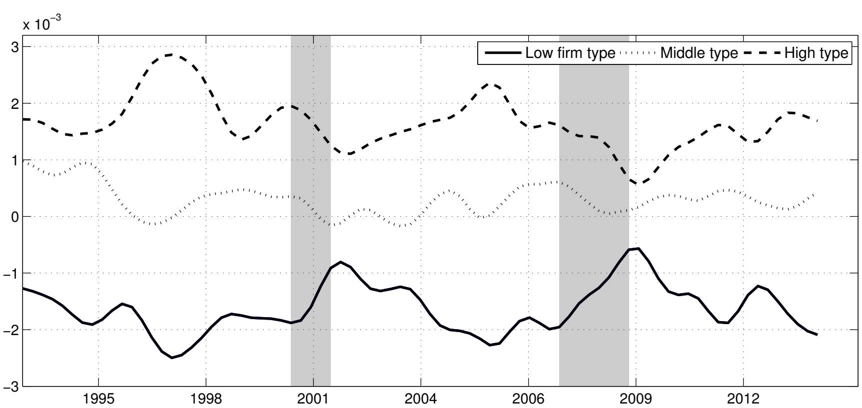
(a) Workers: Nonemployment



(b) Firms: Nonemployment



(c) Firms: Poaching



Notes: Productivity terciles calculated off of average revenue productivity.