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 over time using U.S. linked employer-employee data. Composition changes of workers and firms move in opposite directions over the business cycle. During and after recessions, low-rank workers are less likely to work, while the employment share of low-rank firms increases. The agreement between worker and firm ranks increases in the early stages of labor market downturns. We consider these results in the context of a model of cyclical labor market sorting.

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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 by Kahn (2010), Oreopoulos, von Wachter, and Heisz (2012), and Abel and Deitz (2019) have shown that college graduates obtain relatively low-skill jobs during labor market downturns. This disconnect between the workers and their job best matches is what Barlevy (2002) called the "sullying" effect of recessions. Barlevy (2002) also emphasized that, during labor market downturns, a lower rate of voluntary quits for better employment can cause workers to spend more time in worse matches.

Such a sullying effect of recessions contrasts with the more conventional "cleansing" effect.[1] This mechanism suggests that, during economic downturns, the least productive jobs 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 distributions of workers and firms, and the sorting of workers between firms.

In this paper, we provide evidence on the cleansing and sullying effects of recessions on workers, firms, and sorting in the labor market. We use matched employer-employee data to estimate several different methods of ranking workers and firms to establish how labor market sorting (i.e., the degree to which low- vs. high-rank workers work at low- vs. high rank-firms) varies over the business cycle. We find that, regardless of the ranking method, recessions are times when the employment distribution shifts towards high-rank workers. This cleansing effect on the worker distribution is fairly intuitive. Somewhat more surprising are the firm quality dynamics. We find evidence of a sullying effect on the firm quality distribution. The firm quality distribution shifts down in recessions, as low-rank firms take a larger share of employment. Although several mechanisms are at work, positive sorting strengthens during recessions. We consider these cleansing, sullying, and sorting effects of recessions in the context of the model of cyclical labor market sorting proposed by Lise and Robin (2017).[2]

We present evidence on how labor market sorting varies over the business cycle. To do so, we

[1] See Caballero and Hammour (1994). Note that Barlevy (2002) considered both the cleansing and sulling effects of recessions.

[2] We therefore consider models in which both workers and firms contribute directly to output. A separate literature that includes Eeckhout and Sephasalari (2018) and Herkenhoff, Phillips, and Cohen-Cole (2019) introduce cyclicality into models of two-sided heterogeneity by introducing workers that differ in their assets and therefore search behavior. This approach affects the value of job matches without changing the productivity of particular worker-firm matches.

make use of the insights of many contributions on sorting in the labor market that exploit the unique properties of universe-level linked employer-employee data. We implement four methods of ranking workers and firms using quarterly linked employer-employee data for 11 U.S. states for 1994-2014. Each of these methods involves ordering workers and firms along a univariate, time-invariant ranking.[3] In other words, we assume that workers and firms are of high or low intrinsic rank along a single dimension. We start with methods that rank workers and firms independently from each other. We rank workers based on the time spent in employment vs. nonemployment, as well as by their average earnings when working. Following Bagger and Lentz (2019), we rank firms based on their share of hires from poaching. Motivated by the recent work of Bartolucci, Devicienti, and Monzón (2018) and Haltiwanger, Hyatt, and McEntarfer (2018), we rank firms by labor productivity (revenue per worker, with industry adjustments to capture differences in value added). We also rank workers and firms by assuming that earnings are an additive function of a worker effect and a firm effect as in Abowd, Kramarz, and Margolis (1999). Finally, we implement a ranking algorithm that follows Hagedorn, Law, and Manovskii (2017) and Lopes de Melo (2018), whose methods are motivated by labor market search models. In total, we implement four methods of ranking workers and firms on our linked employer-employee data. We focus on changes in composition and sorting using employment-weighted terciles (i.e., low, middle, and high) of the worker and firm rank distribution.

All four methods of ranking workers and firms yield qualitatively similar results on worker composition, composition, and sorting. Low-rank workers are most affected by labor market downturns. Although both low-rank and high-rank workers have fewer net flows from nonemployment in worse labor markets, changes in the nonemployment transition rate are more severe for low-rank workers. Thus, recessions are times when the composition of the workforce shifts away from low-rank workers. Every percentage point increase in the unemployment rate is associated with a 0.114 to 0.449 percentage point decline in the employment share of workers ranked in the lowest tercile.[4] This result can be characterized as a cleansing effect. During labor market downturns, the most productive workers are most able to compete for scarce jobs. Many potential job opportunities for low-rank workers are no longer profitable in worse states of the economy. This result echoes work by Oi (1962), Okun (1981), and van Ours and Ridder (1995) on the relative cyclicality of worker employment by skill, quality,

[3] Recent studies by Şahin et al. (2014) and Lindenlaub and Postel-Vinay (2016) explore multi-dimensional models of worker and firm sorting.

[4] All results in this paper are quarterly unless otherwise noted.

and education.

During labor market downturns, sullying effects drive changes in firm composition. Especially in the times of high unemployment that follow recessions, there an increase in the employment share of low-rank firms. Every additional percentage point of the unemployment rate above its HP trend is associated with a 0.054 to 0.063 percentage point increase in the employment share of firms ranked in the lowest tercile. We show the central importance of the cyclical job ladder, which generates an increase in employment at low-rank firms through differential poaching as opposed to nonemployment.[5] We find that the net nonemployment hiring of low-rank and high-rank firms adjust similarly in times of high unemployment. Each additional percentage point of the unemployment rate above its HP trend is associated with a decline in net hiring from nonemployment of 0.102 to 0.122 percentage points for low-rank firms, and 0.091 to 0.109 percentage points for high-rank firms. This differential nonemployment response of 0.010 to 0.028 percentage points favors high-rank firms. However, this difference is small compared to the difference between the net poaching responses of low-rank and high-rank firms. For low-rank firms, net hires from poaching *increase* by 0.060 to 0.076 percentage points, while those of high-rank firms *decrease* by 0.035 to 0.065 percentage points. This differential poaching response of 0.111 to 0.130 percentage points strongly favors low-rank firms. Therefore, the increase in the employment share of low-rank firms in times of high unemployment can be attributed to changes in net poaching flows. Our paper links the cyclical job ladder, considered by Haltiwanger et al. (2018), Haltiwanger, Hyatt, and McEntarfer (2018), and Moscarini and Postel-Vinay (2018) to employment composition by firm type.[6] During labor market downturns, workers spend more time in worse jobs.

Cyclical changes in labor market sorting naturally follow from these composition changes. We explore the frequency with which workers of different ranks are employed at firms of different ranks.[7]

[5]The cyclical job ladder references the procyclical rate at which workers voluntarily quit their jobs for better matches. This process by which workers obtain a series of better matches is often called "climbing the job ladder." For a reivew of the literature on the cyclical job ladder, see Moscarini and Postel-Vinay (2018).

[6]Of papers on the cyclical job ladder, ours is most similar to Haltiwanger, Hyatt, and McEntarfer (2018) who consider rank workers based on education and firms by within-industry productivity and study transitions in the 2007-2009 recession, along with the expansions that precede and follow it. They find that workers of all education levels move from low productivity to high productivity firms, and do so more frequently during expansions. 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 enter employment from nonemployment. Haltiwanger, Hyatt, and Mcentarfer (2018) focus on the cyclicality of transition rates, and do not consider aggregate composition or directly measure the degree of agreement between worker and firm ranks.

[7]Only a small number of studies, including Bagger, Sørensen, and Vejlin (2013), consider how sorting evolves in linked employer-employee data over time.

Labor market downturns are times when low-rank workers are less likely to work at high-rank firms. Specifically, a one percentage point increase in the unemployment rate is associated with a 0.041 to 0.181 percentage point decrease in the share of low-rank workers at high-rank firms. This change for low-ranked workers is driven by a slowdown in the job ladder: differential changes in net poaching flows into low- vs. high-ranked firms are larger than differential changes in net nonemployment flows. This decline in the share of low-rank workers at high-rank firms strengthens the agreement between worker rank and firm rank. By contrast, high-rank workers are more likely to work at low-rank firms during labor market downturns. A one percentage point increase in the unemployment rate is associated with a 0.023 to 0.098 percentage point increase in the share of high-rank workers at low-rank firms. The slowdown in the job ladder drives this change. The countercyclical increase in the share of high-rank workers at low-rank firms weakens the agreement between worker rank and firm rank. Overall, the mechanisms that strengthen labor market sorting dominate and the agreement between worker rank and firm rank increases slightly. This increase in rank agreement is more apparent in recessions than in the times of high unemployment that follow recessions. Overall, our paper provides evidence of small, countercyclical increases in positive sorting between workers and firms.

We consider our findings in the context of the model of cyclical labor market sorting proposed by Lise and Robin (2017). Their model includes heterogeneous worker and firms, on-the-job search, and business cycles. We show that their framework does not automatically generate all of the cyclical changes in composition that we document. Ranking workers by nonemployment duration using the parameter estimates in Lise and Robin (2017) yields countercyclical cleansing that is nearly identical to what we estimate from linked employer-employee data. However, we find considerable differences on cyclical changes in composition by firm rank. The baseline parameter estimates of Lise and Robin (2017) produce countercyclical cleansing movements away from firms with relatively high poaching hire shares, which contrasts to what we find in our linked employer-employee data. We re-estimate the model to explicitly target the changes in worker and firm shares produced by our estimates on linked employer-employee data. This exercise highlights the implications of our empirical findings for the mechanisms that drive cyclical labor market composition and sorting. We draw two main lessons.

First, in order to generate countercyclical cleansing of the worker distribution and sullying of the firm distribution, then workers must drive the match value of output. This is consistent with the empirical literature that uses linked employer-employee data to estimate additive models of worker and firm effects starting with Abowd, Kramarz, and Margolis (1999), as summarized recently by

Card et al. (2018). This feature is also consistent with the estimated production function from models of labor market sorting, including Lise and Robin (2017). Our findings highlight the importance of worker heterogeneity in driving cyclical labor market composition and sorting.

Second, the set of firms in operation needs to be relatively time-invariant. This does not necessarily follow from the model of Lise and Robin (2017), in which firm composition is determined by a free entry condition. Since firms drive relatively little of the match value of output, the composition of firms can vary a lot without a large effect on the level or dispersion of aggregate output, the unemployment rate, or other moments targeted for model estimation. Our parameter estimates targeting our composition moments from linked employer-employee data yield a more diffuse worker distribution, and a more diffuse and stable cyclical distribution of vacancies by firm type. When the model matches the estimates from of our linked employer-employee data, the sullying effect on the firm distribution outweighs the cleansing effect.

The remainder of this paper proceeds as follows. Next, in Section 2, we describe our data and worker ranking methods. Thereafter, in Section 3, we explore how labor market composition and sorting evolves over time and with labor market conditions. We then consider our empirical estimates in the context of the Lise and Robin (2017) model of cyclical sorting in Section 4. A brief conclusion follows in Section 5.

2 Data

2.1 Source data

The Longitudinal Employer-Household Dynamics (LEHD) linked employer-employee data allows us to explore cyclical labor market composition and 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, see Abowd et al. (2009).[8] We use these data to link workers and firms over time. Because different states enter the LEHD microdata at different times, we use a consistent set of eleven states with data available from 1994-2014.[9]

Recent enhancements to the LEHD data have facilitated the measurement of employer-to-employer

[8]Note that we do not observe self-employment or work for the federal government.

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

transitions. We follow the approach to measuring employer-to-employer transitions in Hyatt et al. (2014).[10] 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. If the worker has a quarter without earnings, then any flows into or from employment are considered flows into and from nonemployment.

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. We provide here a brief overview of each of the methods of measuring the extent and cyclicality of sorting.[11] All ranks are calculated on an employment-weighted basis.

We start by ranking workers and firms based on simple summary statistics. Our first method ranks workers and firms in ways that do not rely directly on observed earnings. We rank firms based on the share of the workers that they hire that come from other firms vs. from nonemployment, following Bagger and Lentz (2019).[12] A firm's poaching (i.e., employer-to-employer transition) hires as a share of all hires is a rough metric for how desirable a firm is as an employer. This measure is, in principle, inclusive of wage and salary compensation, as well as nonwage amenities.[13] To rank workers, we use the fraction of their careers that they spend in employment vs. nonemployment. We count workers who are more frequently employed as being more productive.[14] Specifically, we regress employment on a set of year of birth by quarter dummies, separately by gender, and then rank workers based on the average of the residuals from that regression. This method also yields ranks that have a straightforward interpretation in the model of Lise and Robin (2017). These methods identify the workers who are more likely to encounter a productive match with the firms operating in the economy, and the firms

[10] For exact definitions, see Appendix A.

[11] For additional details on our ranking methods, see Appendix B.

[12] Appropriate caution in interpreting our results is warranted because Bagger and Lentz (2019) do not consider aggregate uncertainty.

[13] More computationally intensive approaches of ranking firms using employer-to-employer transitions have been proposed by Sorkin (2018) and Lentz, Piyapromdee, and Robin (2018).

[14] This method serves as a measure for worker quality because workers with less to gain from working might spend less time doing so. Bagger and Lentz (2019) use unemployment duration as a method of ranking workers in Section 4.2.1 of their paper, although they do not place as much emphasis on this method of ranking workers as they do their poaching hire method of ranking firms.

who are likely to offer workers a more productive job. These methods of ranking workers and firms also run quickly in our model-simulated environment. For these reasons, we target these moments in our quantitative exercise in Section 4.

Our second method ranks workers by their earnings and firms by labor productivity. For raking workers, we us average earnings regressed on year of birth by quarter dummies. Note that this measure of average regression-adjusted worker earnings also provides the initial guess of a worker's rank in our third and fourth ranking methods. For firms, we use revenue from the U.S. Census Bureau's Business Register, in the spirit of the recent work by Haltiwanger et al. (2017).[15] We use this firm-level revenue data to calculate the deviation of a firm from the employment-weighted industry average revenue per worker. We then obtain a measure of labor productivity by adding this firm-level measure to industry-level value added per worker as published by the Bureau of Economic Analysis.

Our third method ranks workers and firms using a model that assumes that earnings are an additive function of a firm effect and worker effect as in Abowd, Kramarz, and Margolis (1999). This specification has recently been used by Card, Cardoso, and Kline (2016) to measure the degree of sorting in the labor market. To overcome estimation issues that follow from the fact that we only observe workers at different parts of their life-cycles, we first regress earnings on a set of year of birth by quarter in time dummies (e.g., born in 1965 and working in 1997Q1). Then, we employ an iterative method to identify worker effects, firm effects, and updated birth cohort by quarter effects.

Fourth, we apply a technique inspired by the recent work of Hagedorn, Law, and Manovskii (2017) and Lopes de Melo (2018). These techniques provide solutions to the inconsistency between the identification assumptions of Abowd, Kramarz, and Margolis (1999) and standard models of labor market search.[16] 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 rank, and then taking the difference between earnings received and this implied reservation

[15] Major differences between our revenue measure and that of Haltiwanger et al. (2017) is that we use revenue data starting in 1994, and include all industries. We also complete these data via imputation. For additional details, see Appendix Section B.2.2.

[16] Readers should note that the random search models proposed by Hagedorn, Law, and Manovskii (2017) and Lopes de Melo (2018) do not consider aggregate uncertainty. Therefore appropriate caution is required in interpreting our cyclical results as they do not have a direct interpretation in the context of the models that correspond to their ranking strategies. However, we think that the computational strategies proposed by these authors, which make intensive use of linked employer-employee data, are helpful in assessing the robustness of our overall findings.

wage. Firms with a greater difference between earnings paid and the reservation wage have a greater surplus from a match and are considered to be more productive.

3 Empirical evidence on composition and sorting

3.1 Overview and notation

In this section, we document how the sorting of workers into firms of different ranks varies over the business cycle. We seek to characterize how the composition of employed workers and firms, as well as labor market sorting, varies with labor market conditions. We have several outcomes of interest: the share of employment that workers and firms of different ranks constitute, and the relative frequency of particular combinations of worker and firm ranks (i.e., the degree of sorting). We also measure the worker flows into and from nonemployment and poaching flows across firms that account for these changes in shares. For these exercises, we characterize the health of the labor market using the difference of the unemployment rate from its HP trend, as well as the first difference in the unemployment rate, following Haltiwanger et al. (2018). These transformations of the unemployment rate serve as our cyclical indicators. The first-difference of the unemployment rate surges during NBER recessions. The difference in unemployment from its HP trend is a measure of times of low vs. high unemployment. We rank firms and workers into three terciles: low, middle, and high based on an employment-weighted ranking of workers and firms across all quarters. We have data from 1994-2014, which allows us to consider two economic contractions: the 2001 and 2007-2009 recessions, as well as the expansions that precede, separate, and follow them.

We introduce some notation to document how employment evolves over time, which builds on the framework of Haltiwanger et al. (2018). Let E_{ijt} denote the number of workers of rank tercile i working at firms of rank tercile j at time t.[17] Employment for each worker i firm j category changes from time $t-1$ to t due to separations to nonemployment N^s_{ijt}, hires (accessions) from nonemployment N^a_{ijt}, separations from poaching (i.e., employer-to-employer transitions) P^s_{ijt}, and poaching hires P^h_{ijt}.[18] Specifically, the change in employment can be expressed as

$$\Delta E_{ijt} = E_{ijt} - E_{ijt-1} = N^a_{ijt} - N^s_{ijt} + P^a_{ijt} - P^s_{ijt}. \tag{1}$$

[17]Throughout Section 3, the terms “worker rank” and “firm rank” refer their respective terciles.

[18]For formal definitions, see Appendix A.3.

The change in employment for any worker-firm group can be expressed as the sum of net hires from nonemployment $N^a_{ijt} - N^s_{ijt}$ and net hires from poaching $P^a_{ijt} - P^s_{ijt}$. We further express the sum of workers of rank i across firms of any rank at time t as $E_{i\bullet t}$, and analogously express totals for firm rank j as $E_{\bullet jt}$. Total employment at time t, $E_{\bullet\bullet t}$ is written E_t. Note that poaching flows do not change the total employment of any worker rank and so $\Delta E_{i\bullet t} = N^a_{i\bullet t} - N^s_{i\bullet t}$. This is because an employer-to-employer transition implies a separation of a worker of rank i from one employer and a hire of a worker of that same rank at a different employer. Net poaching flows, however, can affect the composition of firms.

3.2 Worker and firm composition

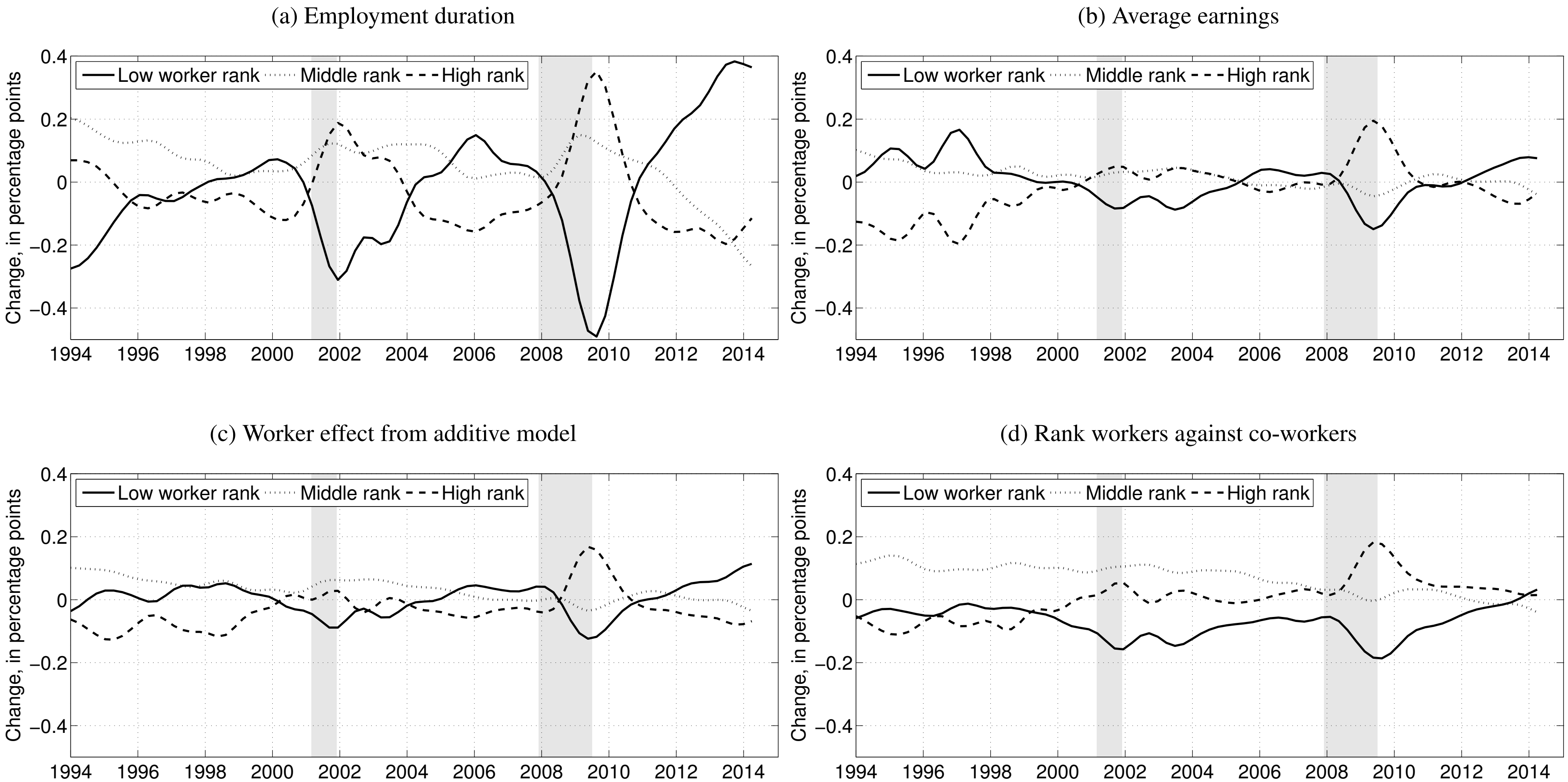
3.2.1 Worker composition

We now document how worker composition evolves over time. By construction, low-, middle-, and high-rank workers will on average each have a share of one-third. However, in any given quarter the shares of employment in these terciles can differ from one-third. From one quarter to another, workers with a time-invariant rank enter and leave employment, and these transitions determine how the employment shares of these different groups evolve over time. For example, if more workers of high-rank enter employment than other groups, the high-rank group will gain as a share of employment.

The evolution of the employment shares of low, middle, and high-rank workers is shown in Figure 1. We plot the quarterly change in the share of employment of workers of different ranks, using each of our four ranking methods. In terms of the notation introduced in Section 3.1, we plot $E_{i\bullet t}/E_t - E_{i\bullet t-1}/E_{t-1}$.[19] For example, see Panel 1(a), which shows how the shares of employment change for each tercile when we rank workers by their employment duration. A positive value indicates that a rank tercile is gains as a share of employment, while a negative value indicates that a rank tercile is loses some of its share. In 2005Q4 (during an economic expansion), the share of low-rank workers increases by 0.15 percentage points, the share of middle-rank workers increases by 0.01 percentage points, and the share of high-rank workers declines by 0.16 percentage points. It is apparent from Figure 1 that the middle and late periods of economic expansions are time when low-rank workers gain as a share of employment, and the share of high-rank workers declines. During and after recessions, the employment share of high-rank workers increases, as that of low-rank workers decreases.

[19] The changes in the shares for each of the three groups add to exactly zero prior to seasonal adjustment.

Figure 1: Changes in worker rank shares



Notes: Shaded regions indicate recessions. Data seasonally adjusted and Henderson-filtered using X11.

Cyclical changes in worker composition are similar in direction across the different ranking methods, but the largest changes are found when we rank workers by their employment duration as in Panel 1(a). Panel 1(b) shows how the shares of the employment evolve when workers are ranked by average earnings. Panel 1(c) shows how the shares evolve over time when workers are ranked based on the worker effect from our additive model of earnings with worker and firm effects. Panel 1(d) shows how composition evolves for workers initially ranked by average earnings, but then re-ranked to ensure that more productive workers at the same firm earn more than their less productive co-workers. Overall, the changes in the shares in these terciles are very small, with the share of workers moving up or down by less than 0.5 percentage points over the span of a quarter. The largest movements occur around the two recessions, where the share of workers in the highest tercile increases, largely at the expense of the workers in the lowest tercile.

Shifts from low-rank to high-rank workers occur most rapidly at the end of each of the recessions. The magnitude of these changes differs somewhat by the ranking method we use. In 2001Q4, the last quarter of the 2001 recession, 0.31 percent of employment shifted away from workers in the lowest tercile of employment duration, while those workers with the highest employment duration increase their share of employment by 0.19 percent, see Panel 1(a). Panel 1(b) shows that, in the same quarter, the employment share of the lowest earnings workers decreases by 0.08 percentage points, and that of the highest earnings workers increases by 0.05 percentage points. Panel 1(c) shows that the employment share of workers with a low additive effect decreases by 0.09 percentage points, while that of workers with a high additive effect increases by 0.03 percentage points. Panel 1(d) reports that those workers who have a low rank after being compared to their co-workers lose 0.16 percentage points of employment, and those who have a relatively high rank increase their employment share by 0.05 percentage points.[20]

The shift from low-rank and toward high-rank workers is greater in the more severe 2007-2009 recession. In 2009Q2, the last quarter of the 2007-2009 recession, the employment share of the lowest terceile of workers ranked by employment duration decreased by 0.49 percentage points, while that of workers with a high employment duration increased by 0.35 percentage points (Panel 1(a)). In

[20] There is a decrease in the share in the low tercile and an increase in the high tercile that precedes the 2001 recession as well. This is attributable to the strong increase in real earnings in the late 1990s in the U.S., see Hahn, Hyatt, and Janicki (2019). Despite having time dummies for birth cohorts by quarter, the ranking methods that we use generally show entrants as more productive than exiters in the context of this surge in real earnings. Note that the method that uses employment duration does not show this increase, see Panel 1(a), in contrast to the other three methods in which the worker rank is a transformation of worker earnings.

Table 1: Changes in worker rank shares and the unemployment rate

	Employment duration	Average earnings	Additive model worker effects	Rank workers vs. co-workers
	Difference in unemployment from its HP trend			
Low	-11.2***	-3.0**	-3.2**	-2.7***
	(2.7)	(1.4)	(1.2)	(1.0)
High	7.4***	2.1	2.4**	2.2**
	(2.0)	(1.4)	(1.1)	(0.9)
	First-difference of the unemployment rate			
Low	-44.9***	-13.9***	-12.6***	-11.4***
	(5.0)	(3.2)	(2.7)	(2.3)
High	31.6***	16.9***	14.8***	12.9***
	(3.9)	(2.7)	(2.2)	(1.7)

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. To avoid excessive decimal places, the dependent variables range from $[-100, 100]$, while the cyclical indicators range from $[-1, 1]$.

that same quarter, the employment share of workers with relatively low earnings declined by 0.14 percentage points, while that of workers with high earnings increased by 0.18 percentage points (Panel 1(b)). The employment share of workers with a low additive effect declined by 0.12 percentage points, while those with a high additive effect increased by 0.16 percentage points (Panel 1(c)). The employment share of workers have a low rank after being compared to their co-workers declined by 0.19 percentage points, while those who have a relatively high rank increased by 0.18 percentage points (Panel 1(d)). These changes are similar in direction and roughly twice as large as those that occurred in 2001Q4. This shift away from the lowest worker tercile toward the highest continues, albeit more slowly, in the years that follow each of the recessions.

Table 1 shows how the share of employment by worker rank changes with our cyclical indicators. Specifically, we regress $E_{i\bullet t}/E_t - E_{i\bullet t-1}/E_{t-1}$ on our seasonally-adjusted cyclical indicators, season dummies, and a time trend.[21] This table summarizes the cyclical features of Figure 1. Changes in worker composition are greatest during recessions, rather than the times of high unemployment that follow recessions. Consistent with these features of Figure 1, point estimates in Table 1 are greater in

[21] Similar specifications have been used to measure the cyclicality of job ladders in the labor market by, among others, Haltiwanger et al. (2018).

magnitude for the first-difference of the unemployment rate than the difference of the unemployment rate from its HP trend.

Figure 1 also indicates that workers ranked by employment duration show larger cyclical changes than when ranked by other methods. Consistent with this, Table 1 shows that composition is most cyclically sensitive when workers are ranked by employment duration. Specifically, it shows that one percentage point increase in the unemployment rate is associated with a declines of 0.449 percentage points in the share of workers with a low employment duration, and a 0.316 percentage point increase in the share of workers with a high employment duration. For every additional percentage point that the unemployment rate is above its HP trend, the low employment duration worker share declines by 0.112 percentage points, and the high employment duration share increases by 0.074 percentage points. Table 1 also shows that the other three methods of ranking workers (earnings, worker effect, and reranking against co-workers) exhibit less cyclical sensitivity.[22] A one percentage point increase in the unemployment rate is associated with a 0.12 to 0.14 decline in low ranked workers and a 0.12 to 0.17 percentage point increase in the share of high-rank workers. An additional percentage point of the unemployment rate above its HP trend is associated with a 0.027 to 0.032 percentage point decline in the employment share of low-rank workers, and a 0.021 to 0.024 percentage point increase in the share of high-rank workers.

Table 2 explores the transition dynamics that underlie these cyclical shifts in employment composition by worker rank. Specifically, it shows how net hiring from nonemployment changes with labor market conditions. The net nonemployment variable we define is $(N^a_{i\bullet t} - N^s_{i\bullet t})/((E_t + E_{t-1})/2)$.[23] Keeping the denominator on the same scale as in Table 1 allows us to sum nonemployment rates across worker groups to express the total change in employment and more easily interpret changes in the share of employment across worker groups.[24] The differential between the nonemployment transition rates of high-rank and low-rank workers is, by construction, close to the differential between the changes in the shares for those groups.

Ranking workers by employment duration, cyclical changes in net nonemployment transitions are concentrated among low-rank workers. When the unemployment rate increases by one percentage

[22] In interpreting the difference between the employment duration and other ranking methods, it is helpful to note that workers spending time in nonemployment are especially likely to do so during recessions, and so its especially strong relationship is at least partially mechanical.

[23] Appendix Figure C1 shows the time series of this measure for each worker group.

[24] To see this, note that our net nonemployment measure is equivalent to $(E_{i\bullet t} - E_{i\bullet t-1})/((E_t + E_{t-1})/2)$.

Table 2: Net nonemployment hiring by worker rank and unemployment

	Employment duration	Average earnings	Additive model worker effects	Rank workers vs. co-workers
	Difference in unemployment from its HP trend			
Low	-21.4***	-13.5***	-13.9***	-13.1***
	(5.1)	(3.3)	(2.9)	(2.8)
High	-1.7	-7.7***	-8.0***	-8.3***
	(1.6)	(2.7)	(2.4)	(2.3)
	First-difference of the unemployment rate			
Low	-83.0***	-56.4***	-51.3***	-48.7***
	(10.0)	(6.0)	(5.5)	(5.3)
High	-2.8	-27.8***	-23.0***	-25.6***
	(4.0)	(6.1)	(5.8)	(5.4)

Notes: Estimates of change in 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. To avoid excessive decimal places, the dependent variables range from $[-100, 100]$, while the cyclical indicators range from $[-1, 1]$.

point, net nonemployment flows of low-employment workers decline by 0.830 percentage points, while flows of high-employment workers only decline by 0.028 percentage points. Methods of ranking workers that rely on transformations of earnings rather than employment show smaller differences between low- and high-rank workers. There are sizeable declines in net nonemployment flows for both low- and high-rank workers, and declines in these transitions are greater in magnitude for low-rank workers. In these three methods, a one percentage point decrease in the unemployment rate is associated with a 0.487 to 0.564 percentage point decline in net nonemployment flows of low-rank workers, but only a 0.230 to 0.278 percentage point decline for high-rank workers.

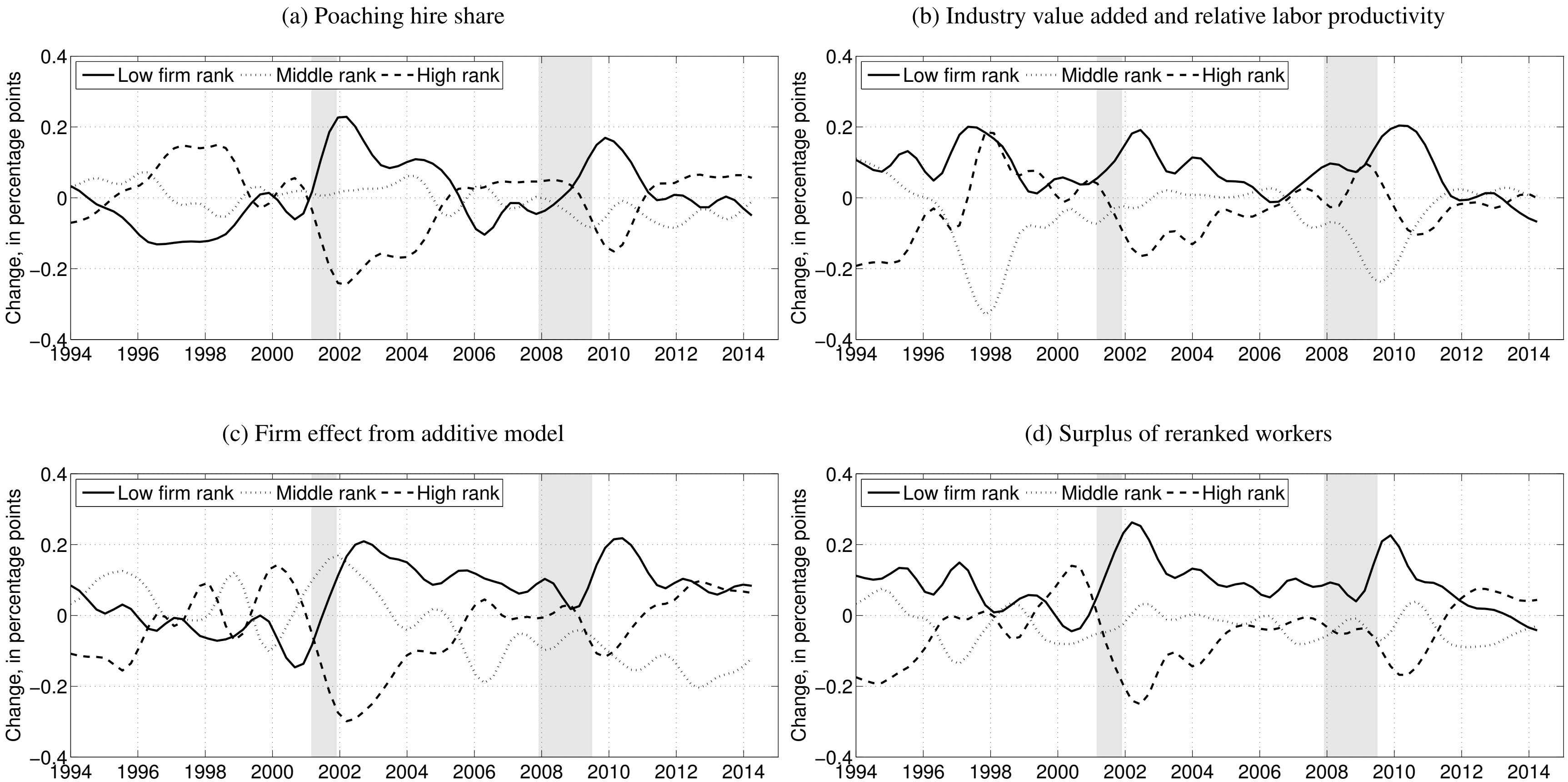
As with worker composition, changes in net nonemployment flows are more closely aligned to recessions (i.e., the first-difference of the unemployment rate) than times of high unemployment (i.e., HP-detrended unemployment). An additional percentage point of the unemployment rate above its HP trend is associated with a decline of 0.214 percentage points in the share of workers with a low employment duration, but a decline of only 0.017 percentage points for high-rank workers. Methods that rely on a transformation of worker earnings show declines in low-rank worker nonemployment flows of 0.131 to 0.139 percentage points, while high-rank worker nonemployment flows decline by only 0.077 to 0.083 percentage points. This exercise provides insight into the mechanisms that generate cyclical changes in employment shares as documented in Table 1. The high-rank worker tercile exhibits a relatively small countercyclical decline in net nonemployment flows, and so its share of employment increases.

Our results on the cyclical worker composition tell a consistent story and have an intuitive interpretation. In all four of our ranking methods, recessions are times when the employment distribution shifts away from low-rank workers and towards high-rank workers. This result can be understood as a cleansing effect on the worker distribution. During economic expansions, increasing employment requires hiring relatively unproductive workers. When the economy contracts, there are fewer jobs available. The more productive workers are better able to compete for scarce jobs. Therefore, the employment share of more productive workers increases while that of less productive workers declines.

3.2.2 Firm composition

We now explore how the employment shares of differently ranked firms change over time. Figure 2 shows quarterly changes in firm composition over time, using each of our four ranking methods. In the average quarter, each tercile accounts for one-third of employment, but this share changes over time. We plot the change in employment share $E_{\bullet jt}/E_t - E_{\bullet jt-1}/E_{t-1}$ for each firm tercile j. For example, Panel 2(a) shows how firm composition evolves when firms are ranked by poaching hire share. In 2005Q4, firms with a relatively low poaching hire share lost 0.09 percent of employment, those with a middle rank gained 0.03 percent of employment, and those with a high poaching share gained 0.02 percent of employment. Panel 2(b) shows how firm composition evolves when firms are ranked by labor productivity. Panel 2(c) shows how firm composition evolves when firms are ranked by their effect from an additive model. Panel 2(d) shows how firm composition evolves when firms are ranked by match surplus implied by the earnings of workers re-ranked against their co-workers. Most of the movements are small, with each tercile's share rarely changing by more than 0.2 percentage points. The exceptions occur during and after each of the two recessions. In expansions, the high-rank firm tercile slowly increases its share of employment, and the share of low-rank firms decreases. During and after the 2001 and 2007-2009 recessions, employment quickly shifts away from high-rank firms and toward low-rank firms.

Figure 2: Change in firm rank shares



Notes: Shaded regions indicate recessions. Data seasonally adjusted and Henderson-filtered using X11.

Changes in employment composition by firm rank are at their most rapid in the quarters that follow each of the recessions. For example, when we rank firms by their poaching hire shares in Panel 2(a), the largest increase in the employment share of low-rank firms occurs in 2002:Q1, when such firms gain 0.23 percentage points of employment. These gains are largely at the expense of the high-rank firms, who lose 0.25 percentage points. These shifts are qualitatively similar in the other ranking methods. In 2002:Q1, the lowest tercile of firms ranked by labor productivity gains 0.18 percentage points of employment, while the highest loses 0.14 (Panel 2(b)). The lowest tercile of firms ranked by their additive effect gains 0.19 percentage points, and the highest tercile loses 0.30 percentage points (Panel 2(c)). The lowest tercile of firms ranked by the surplus implied by workers ranked against their co-workers gains 0.27 percentage points, and the highest tercile loses 0.24 percentage points (Panel 2(d)).

Changes in employment shares after the 2007-2009 recession are similar in direction but smaller in magnitude than those that occur just after the 2001 recession. In 2009Q3, the employment share of firms with the lowest share of hires from poaching increases by 0.17 percentage points and that of the highest share of hires from poaching declines by 0.14 percentage points (Panel 2(a)). The employment share of firms with the lowest labor productivity increases by 0.20 percentage points, and that of the highest productivity firms declines by 0.09 percentage points (Panel 2(b)). The employment share of firms with the lowest additive effects increases by 0.19 percentage points, and that of the highest effects increases by 0.12 percentage points. The employment share of firms with the lowest average surplus implied by workers ranked against their co-workers increases by 0.23 percentage points, while those with the highest implied average surplus increases by 0.14 percentage points.

Table 3 measures how firm composition varies with the unemployment rate. Each specification regresses the outcome of interest $E_{\bullet jt}/E_t - E_{\bullet jt-1}/E_{t-1}$ on the unemployment rate (either the difference from its HP trend or its first-difference), as well as a linear time trend and season dummies. Labor market downturns are associated with an increase in the employment share of low-rank firms, and a corresponding decline for high-rank firms. The change in employment composition by firm rank is qualitatively consistent across ranking methods when we use the HP-detrended unemployment rate as our cyclical indicator, i.e., when we measure times of low vs. high unemployment. For every additional percentage point difference of the unemployment rate from its HP trend, the employment share of low-rank firms increases by 0.055 to 0.063 percentage points, and that of high-rank firms decreases by 0.041 to 0.072 percentage points.

Table 3: Changes in firm rank shares and the unemployment rate

	Poaching share of hires	Labor productivity	Additive worker & firm effects	Surplus of reranked workers
	Difference in unemployment from its HP trend			
Low	6.3***	5.0***	5.5***	5.4***
	(2.2)	(1.3)	(1.5)	(1.4)
High	-6.9***	-4.1***	-6.6***	-7.2***
	(1.8)	(1.5)	(1.8)	(1.7)
	First-difference of the unemployment rate			
Low	12.0**	8.2**	2.0	9.0**
	(5.5)	(3.4)	(3.9)	(3.6)
High	-8.9*	5.5	-8.5*	-6.6
	(4.7)	(3.7)	(4.7)	(4.5)

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. To avoid excessive decimal places, the dependent variables range from $[-100, 100]$, while the cyclical indicators range from $[-1, 1]$.

We find more differences between ranking methods when we consider how firm composition response to the first-difference of the unemployment rate, i.e., the changes that align with recessions. The largest effects are found when we rank firms by their poaching hire share. A one percentage point increase in the unemployment rate is associated with a 0.120 percentage point increase in the share of employment share of firms with a low poaching share, and a 0.089 percentage point decrease in that of firms with a high poaching share. Ranking firms by labor productivity, we find that a one percentage point increase in the unemployment rate is associated with a 0.082 percentage point increase in the employment share of low-rank firms, and a 0.055 percentage point increase in that of high-rank firms. Ranking firms by their additive effects, a one percentage point increase in the unemployment rate increases the employment share of low-rank firms by 0.020 percentage points, decreases that of high-rank firms by 0.085 percentage points. Using our measure of firm surplus, we find that a one percentage point increase in the unemployment rate increases the employment share of low-rank firms by 0.090 percentage points, and decreases that of high-rank firms by 0.066 percentage points. These ranking methods usually have a similar sign and magnitude to the difference of the unemployment rate from its HP trend. However, they are much less precisely estimated. It is only when we rank firms by their poaching share of hires that we obtain parameter estimates that are in opposite directions and both statistically distinct from zero.

An increase in the employment share of low-rank firms during times of high unemployment is a robust empirical finding. Note that these four ranking methods rely on three distinct sets of variables. The poaching hire share ranking method uses transitions. The labor productivity measure uses firm-level revenue and industry-level value added. The other two firm ranking methods rely on earnings. Despite substantial differences in what each ranking method measures, there is an aspect of the labor market that can account for such similarity. Each method identifies a firm's rank in the job ladder. We now explore the role of the cyclical job ladder in explaining the countercyclical increase in the employment share of low-rank firms.

Table 4 measures how poaching and nonemployment transitions for firms of different ranks vary with the unemployment rate. Our dependent variables are $(N^{a}_{\bullet jt} - N^{s}_{\bullet jt})/((E_t + E_{t-1})/2)$ for nonemployment and $(P^{a}_{\bullet jt} - P^{s}_{\bullet jt})/((E_t + E_{t-1})/2)$ for poaching.[25] In worse labor markets, net hiring from nonemployment declines for both low-rank and high-rank firms. Point estimates for the nonemployment response of low-rank firms are consistently greater in magnitude than high-rank firms, although it is usually not possible to reject equality of the coefficients. When the unemployment rate increases by one percentage point, high-rank firms decrease net hiring from nonemployment by 0.301 to 0.351 percentage points, while low-rank firms increase decrease net hiring by 0.404 to 0.518 percentage points. Nonemployment hiring changes are smaller using HP-detrended unemployment as the cyclical indicator. Although the point estimates for this response are consistently greater in magnitude for high-ranked firms, they are not statistically distinct in any ranking method. For every additional percentage point of the unemployment rate above its HP trend, net hiring from nonemployment declines by 0.091 to 0.109 percentage points for high-rank firms, and declines by 0.102 to 0.122 for low-rank firms.

Table 4 also measures how net poaching for firms of different ranks vary with the unemployment rate. Here, we find greater differences. Net poaching flows of high-rank and low-rank firms move in opposite directions with out cyclical indicators. In worse labor markets, net poaching flows of high-rank firms decline, while net poaching flows of low-rank firms increase. This difference is because high-rank firms tend to gain employment through poaching, while low-rank firms tend to lose employment through poaching. In worse labor markets, workers move from low-rank to high-

[25] Appendix Figure C2 shows the time series of the net nonemployment measure for each firm tercile, and Appendix Figure C3 shows analogous time series for the net poaching measure.

Table 4: Change in net hiring by firm rank and unemployment

	Poaching share of hires	Labor productivity	Additive model firm effects	Surplus of reranked workers
	Difference in unemployment from its HP trend			
Nonemployment				
Low	-10.2**	-12.2***	-11.9***	-11.9***
	(3.9)	(3.2)	(3.2)	(2.9)
High	-9.1***	-9.4***	-10.9***	-10.7***
	(2.1)	(2.5)	(2.8)	(2.7)
Poaching				
Low	6.0***	7.6***	6.8***	6.5***
	(0.9)	(1.2)	(1.0)	(1.0)
High	-6.5***	-3.5***	-6.2***	-5.9***
	(1.0)	(0.8)	(0.9)	(0.9)
	First-difference of the unemployment rate			
Nonemployment				
Low	-40.4***	-51.8***	-51.2***	-46.6***
	(8.9)	(6.1)	(6.0)	(5.7)
High	-30.1***	-30.2***	-35.1***	-33.3***
	(4.5)	(5.8)	(6.3)	(6.1)
Poaching				
Low	12.7***	11.9***	13.7***	14.8***
	(2.3)	(3.3)	(2.6)	(2.5)
High	-12.7***	-8.5***	-12.3***	-11.2***
	(2.6)	(2.0)	(2.5)	(2.6)

Notes: Estimates of change in 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. To avoid excessive decimal places, the dependent variables range from $[-100, 100]$, while the cyclical indicators range from $[-1, 1]$.

rank firms at a slower pace. When the uenmployment rate increases by one percentage point, net hiring through poaching of high-rank firms declines by 0.085 to 0.127 percentage points. For low-rank firms, it increases by 0.119 to 0.148 percentage points. For every additional percentage point that the unemployment rate is above its HP trend, net poaching of high-rank firms declines by 0.035 to 0.065 percentage points, and that of high-rank firms increases by 0.060 to 0.076 percentage points.

The transition dynamics in Table 4 highlight the role of the cyclical job ladder in changes in employment composition by firm rank. In order for there to be countercyclical increases in the employment share of low-rank firms, the cyclical response of poaching must be greater than that of nonemployment. The net poaching response dominates in the times of high unemployment that follow recessions. Using the difference of the unemployment rate from its HP trend as the cyclical indicator yields a differential net poaching response, which favors low-rank firms is 0.111 to 0.130 percentage points.[26] The net nonemployment response, which favors high-rank firms, is only 0.010 to 0.028 percentage points.[27] In times of high unemployment, there is almost differential net nonemployment response between high-rank and low-rank firms, and so cyclical changes in relative employment are driven by differences in net poaching.

In recessions, the effect of slowdown of the job ladder competes with a larger offsetting effect from nonemployment transitions. Net nonemployment hiring of both low-rank and high-rank firms declines, but the net nonemployment hiring of high-rank firms declines by less. Using the first difference of the unemployment rate, the differential response of the net nonemployment margin of high-rank firms to low-rank firms is 0.103 to 0.216 percentage points.[28] In other words, when unemployment increases, high-rank firms gain employment, on net, from the nonemployment margin. This result is consistent with a cleansing effect of recessions: relatively productive businesses are less affected. However, there is a sullying effect that offsets this cleaning. The differential response of low-rank firms to high-rank firms the net poaching margin is 0.204 to 0.260 percentage points.[29] During recessions, the net nonemployment response, which favors high-rank firms, offsets much of the net poaching response, which favors low-rank firms. This analysis therefore helps us understand the results in Table 3 that use the first-difference of the unemployment rate as the cyclcial indicator. The shift in employment composition from high-rank to low-rank firms begins during recessions, but is most rapid in the year that follows each recession. These are times when output is expanding and unemployment is at a high level and relatively stable.

[26]These differences are calculated using results presented in Table 4 for net poaching that use the HP-detrended unemployment rate as the cyclical indicator. The smallest differential response of net poaching transitions is found when we rank firms by labor productivity, $0.076 + 0.035 = 0.111$. The largest differential net poaching response is found when we rank firms by their additive effect, $0.068 + 0.062 = 0.130$.

[27]These differences are calculated using results presented in Table 4 for net nonemployment transitions that use the HP-detrended unemployment rate as the cyclical indicator. The smallest differential response of net nonemployment transitions is found when we rank firms by their additive effect, 0.119-0.109=0.010. The largest differential net nonemployemnt response occurs when we rank firms by labor productivity, $0.122 - 0.094 = 0.028$.

[28]These differences are calculated using results presented in Table 4 for net nonemployment transitions using the first-difference of the unemployment rate as the cyclical indicator. The smallest differential is found when we rank firms by their poaching hire shares, $.404 - .301 = 0.103$, and the largest when we rank firms by labor productivity, $0.518 - 0.302 = 0.216$.

[29]These differences are calculated using results presented in Table 4 for net poaching that use the first-difference of the unemployment rate as the cyclical indicator. Labor productivity exhibits the smallest differential $0.119 + 0.085 = 0.204$, and the additive and reranking vs. co-worker methods both yield the largest, $0.137 + 0.123 = 0.148 + 0.112 = 0.260$.

This relationship between the cyclical job ladder and employment composition also helps interpret Figure 2. One interesting aspect of these countercyclical increases in the employment share of low-rank firms, common to all four firm ranking methods that we employ, is that the increase during the 2001 recession is larger than that of the 2007-2009 recession. This is despite the fact that the latter recession was more severe, both in terms of output and in the associated decline in the health of the labor market. Cyclical changes in employment composition are determined by how firms of different ranks change their behavior with economic conditions. If the primary means of adjustment is via the poaching margin, there will be a larger increase in the employment share of firms that rank lower on the job ladder. Recall that the nonemployment margin favors high-rank firms. If a recession induces a greater differential nonemployment response, there will be less of a increase in the employment share of low-rank firms. In the 2007-2009 recession, the decline in net nonemployment hiring was especially dramatic, and so there is less of an increase in the employment share of low-rank firms.[30]

Our results on firm composition tell a consistent story across the four ranking methods. We find that the employment share of low-ranked firms increases in the times of high unemployment that follow recessions. This countercyclical sullying of the firm distribution contrasts with the countercyclical cleansing we documented in Section 3.2.1. The cyclical job ladder has a central role in mediating the increase in the employment share of low-rank firms. The differential employment response of low-rank firms in times of high unemployment is driven by the poaching margin. This finding is consistent with the earlier evidence of Haltiwanger et al. (2018), Haltiwanger, Hyatt, and McEntarfer (2018), and Moscarini and Postel-Vinay (2018) on the cyclical job ladder.

3.3 Cyclical worker-firm rank agreement

We now characterize cyclical sorting in the labor market by measuring the agreement between worker and firm ranks. We move from characterizing cyclical changes in workers and firms considered independently to considering the dynamics of worker-firm rank combinations. These joint worker-firm dynamics largely follow these composition changes.

[30]This can be seen in Appendix Figures C1 and C2, which show net poaching and net nonemployment hiring for each firm rank tercile. The changes in net poaching are similar in the 2001 and 2007-2009 recessions. However, the nonemployment response to the 2007-2009 recession is much larger than that of the 2001 recession. The countercyclical shift in employment toward low-ranked firms is determined by the differential poaching response (which favors low-rank firms) relative to the differential nonemployment response (which favors high-rank firms). Therefore, the in the employment share of low-rank firms is greater in the 2001 recession relative to the 2007-2009 recession.

3.3.1 Employment shares of worker-firm rank combinations

We begin our analysis by considering how the shares of employment evolve for our three shares (low, middle, and high) evolve with the labor market.[31] Table 5 quantifies how sorting varies with the unemployment rate. Specifically, the dependent variables in our regressions are $E_{ijt}/E_t - E_{ijt-1}/E_{t-1}$ for each worker tercile i and firm tercile j.[32] In worse labor markets, the employment share of low-rank workers at high-rank firms declines. A one percentage point increase in the unemployment rate is associated with a 0.041 to 0.181 decline in the share of employment of such matches, and an additional percentage point of the unemployment rate above its HP trend is associated with a decline of 0.020 to 0.060 percentage points. In both cases, the effects are largest when workers are ranked by employment duration and firms by poaching. If the share of low-rank workers at high-rank firms declines, this effect increases the agreement between worker and firm rank and therefore strengthens sorting. An analogous change serves to weaken sorting: high-rank workers are more likely to work at low-rank firms in worse labor markets. A one percentage point increase in the unemployment rate is associated with an increase of share of employment of high-rank workers at low-type firms of 0.023 to 0.098 percentage points, and an additional percentage point of the unemplyoment rate above its HP trend is associated with an increased share of 0.018 to 0.026 percentage points. The magnitude of the decline of the share of low-rank workers at high-rank firms is greater than the increase of the share of high-rank workers at low-rank firms, especially during recessions. Therefore, the association between firm rank and worker rank strengthens, on net, among these margins. This suggests a modest increase in worker-firm rank agreement in worse labor markets.

Changes in the share of similarly ranked workers and firms directly affect worker-firm rank agreement. The movements of the share of employment of low-rank workers at low-rank firms shows little cyclical movement. The share of employment of high-rank workers at high-rank firms is highly countercyclical when we use the first-difference of the unemployment rate as our cyclical indicator. The share of employment that consists of high-rank workers at high-rank firms increases by 0.041 to 0.110 percentage points when the unemployment rate increases by one percentage point. This countercyclical increase strengthens positive sorting. The cyclical change of high-rank workers at high-rank firms are mixed when we use the HP-detrended unemployment rate, and estimates range from -0.013 to 0.019 percentage points. An increase in high-rank workers at high-rank firms therefore strengthens

[31] We plot the time series of the changes in the shares of these worker-firm pairs in Appendix Figures C4, C5, and C6.

[32] For the cyclicality of middle-ranked workers and firms, see Appendix Tables C1 and C2.

Table 5: Changes in worker-firm rank shares and unemployment

	Employment & poaching share	Earnings & productivity	Additive worker & firm effects	Ranked workers & surplus
	Difference in unemployment from its HP trend			
Low-rank firms &				
Low-rank workers	-0.7	0.4	0.9	1.1
	(1.3)	(1.0)	(1.0)	(0.7)
High-rank workers	2.6***	1.8***	2.0***	1.8***
	(0.9)	(0.5)	(0.5)	(0.5)
High-rank firms &				
Low-rank workers	-6.6***	-2.0***	-3.0***	-3.0***
	(1.3)	(0.5)	(0.7)	(0.7)
High-rank workers	1.9**	-0.5	-1.2	-1.3*
	(0.8)	(1.0)	(1.0)	(0.7)
	First-difference of the unemployment rate			
Low-rank firms &				
Low-rank workers	-8.3***	0.5	-0.8	0.9
	(3.0)	(2.4)	(2.3)	(1.7)
High-rank workers	9.8***	3.5**	2.3*	4.6***
	(1.9)	(1.3)	(1.3)	(1.3)
High-rank firms &				
Low-rank workers	-18.1***	-4.1***	-9.1***	-6.5***
	(3.1)	(1.3)	(1.6)	(1.7)
High-rank workers	11.0***	10.6***	5.7**	4.1**
	(1.6)	(2.2)	(2.3)	(1.7)

Notes: Estimates of change in 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. To avoid excessive decimal places, the dependent variables range from $[-100, 100]$, while the cyclical indicators range from $[-1, 1]$.

the association between worker rank and firm rank during recessions, but contributes less during the times of high unemployment that follow recessions. Overall, the results of Table 5 show that the agreement between worker rank and firm rank strengthens more during recessions than the times of high unemployment that follow them.

These cyclical changes in labor market sorting follow from the composition changes that we documented in Sections 3.2.1 and 3.2.2, and also provide insights into how these composition changes occur. Some countercyclical changes increase the agreement between worker rank and firm rank, while others cause it to decrease. Labor market downturns are times when low-rank workers are less likely to work. The decline in the employment share of low-rank workers is concentrated at high-rank firms. This decline in the share of low-rank workers at high-rank firms increases the agreement between worker rank and firm rank. By contrast, the increase in the employment share of high-rank workers during economic downturns is concentrated at low-rank firms. This countercyclical change weakens positive sorting. The decline of low-rank workers at high-rank firms is larger than the increase of high-rank workers at low-rank firms, and so agreement increases on net. During recessions, the share of employment of high-rank workers at high-rank firms increases, strengthening sorting, but this effect is not as strong in times of high unemployment. Overall, labor market downturns are times when there is more agreement between worker rank and firm rank, especially during the recessions that initiate these downturns.

3.3.2 Poaching and nonemployment margins

We now explore the role of poaching and nonemployment hiring in generating the changes in employment of particular worker-firm combinations. This analysis can provide insight into what drives countercyclical increases in worker-firm rank agreement. Countercyclical changes in the nonemployment margin are generally driven by cleansing effects. Cyclical changes of worker movements from employment to nonemployment are strongly assocaited with changes in layoffs, see Hyatt et al. (2014). Layoffs occur when worker-firm job matches are no longer profitable. Cyclical changes in nonemployment hiring that differ by worker type can also indicate changes in the value of worker-firm matches. Therefore, we will refer to differential countercyclical declines in nonemployment transitions as the cleansing effects of labor market downturns. In contrast, cyclical changes related to poaching imply a sullying effect. Employer-to-employer transitions (i.e., poaching) is strongly related with worker quits, see Hyatt et al. (2014). Most employer-to-employer transitions involve a voluntary quit for a better job match. Our results explore the cleansing and sullying mechanisms that determine the rank agreement between workers and firms.

Table 6 shows how the net hiring propensity for each worker-firm combination varies with our cyclical indicator. Specifically, we use $(N^a_{ijt} - N^s_{ijt})/((E_{ijt} + E_{ijt-1})/2)$ as our dependent variable. This allows us to assess whether, for workers of a given rank, there is a differential response by firm rank, or whether these are spread rather evenly across firms of different ranks.[33] An additional

[33]This change in the denominator is needed in order to assess cleansing versus sullying effects. Although our worker and firm terciles each have one-third of employment on average, this does not imply that the intersections of these tercile

Table 6: Net nonemployment hires for worker-firm rank shares and unemployment

	Employment & poaching share	Earnings & productivity	Additive worker & firm effects	Ranked workers & surplus
	Difference in unemployment from its HP trend			
Low-rank firms &				
Low-rank workers	-57***	-43***	-42***	-41***
	(16)	(10)	(9)	(9)
High-rank workers	-7	-27**	-25**	-28***
	(11)	(13)	(11)	(9)
High-rank firms &				
Low-rank workers	-70***	-40***	-46***	-46***
	(15)	(10)	(12)	(10)
High-rank workers	-5*	-23***	-29***	-28***
	(3)	(8)	(8)	(8)
	First-difference of the unemployment rate			
Low-rank firms &				
Low-rank workers	-219***	-163***	-155***	-149***
	(35)	(20)	(17)	(17)
High-rank workers	-3	-126***	-114***	-99***
	(26)	(28)	(24)	(20)
High-rank firms &				
Low-rank workers	-251***	-151***	-201***	-158***
	(31)	(20)	(23)	(21)
High-rank workers	-5	-56***	-62***	-68***
	(7)	(20)	(21)	(19)

Notes: Estimates of net poaching 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. To avoid excessive decimal places, the dependent variables range from $[-100, 100]$, while the cyclical indicators range from $[-1, 1]$.

percentage point increase in the unemployment rate is associated with a decline net nonemployment hiring of low-rank workers into low-rank firms of 1.55 to 2.19 percentage points. This range is similar to the response of low-rank workers at high-rank firms, which is from 1.51 to 2.51 percentage points. Two out of our four methods show a cleansing effect for low-rank workers at high-rank firms. When we rank workers by employment duration and firms by their poaching share, the low-rank workers

groups each has one-ninth of employment. In particular, there are relatively few low-rank workers at high-rank firms. In order to measure the differential response, e.g., of low-rank workers at firms of low-rank vs. high-rank, we need to make this adjustment to our denominator.

exhibit a decline of 2.19 percentage points for low-rank firms but by 2.51 percentage points for high-rank firms. When we rank workers and firms based on additive effects, low-rank workers exhibit a decline of 1.55 percentage points at low-rank firms but 2.01 percentage points at high-rank firms. In the other two ranking methods, the responses of low-rank workers to firms of low- and high rank are not statistically distinct from each other. There is somewhat more evidence of a cleaning effect that removes high-rank workers from low-rank firms. When we rank workers by employment duration and firms by poaching hire share, we find essentially no response of high-rank workers at either low- or high-rank firms. The other three ranking methods exhibit a decline of 0.56 to 0.68 percentage points at high-rank firms, but a much higher 0.99 to 1.26 percentage points at low-rank firms. While these results are mixed, we do find some evidence of countercyclical cleaning of low-rank workers at high-rank firms, and of high-rank workers at low rank firms.

There is less evidence of a cleansing effect on worker-firm matches in times of high unemployment. The differential responses for low-rank workers at low-rank vs. high-rank firms are never statistically distinct from zero, nor is there evidence of differential responses for high-rank workers. When we rank workers by employment duration and firms by poaching hire share, we find every additional percentage point between unemployment and its HP trend, net nonemployment flows of low-rank workers at low-rank firms decline by 0.57 percentage points, and at high-rank firms by 0.70 percentage points. The other ranking methods show a decline in net nonemployeemnt transitions of low-rank workers at low-rank firms of 0.41 to 0.43 percentage points, and of 0.40 to 0.46 for high-rank firms. There only a small response of high-rank workers at either low- or high-rank firms, and so the differential response is also negligible. For high-rank workers using the other three ranking methods, we find a response to an additional percentage point of the unemployment rate above its HP trend is associated with a decline in net nonemployment transitions of 0.23 to 0.29 for high-rank firms and 0.25 to 0.28 for low-rank firms. This evidence shows that any cleansing effect on worker-firm rank agreement are concentrated in recessions, rather than the times of high unemployment that follow recessions.

Table 7 shows the net poaching response. Specifically, we use $(P^a_{ijt} - P^s_{ijt})/((E_{ijt} + E_{ijt-1})/2)$ as our dependent variable. The net poaching flows of low-rank workers at high-rank firms declines substantially with the first-difference of the unemployment rate. Specifically, a one percentage point increase in the unemployment rate is associated with a decline in net poaching flows for low-rank workers at high-rank firms of 0.45 to 0.77 percentage points. In contrast, net poaching flows of low-

Table 7: Net poaching hires for worker-firm rank shares and unemployment

	Employment & poaching share	Earnings & productivity	Additive worker & firm effects	Ranked workers & surplus
	Difference in unemployment from its HP trend			
Low-rank firms &				
Low-rank workers	22***	17***	17***	17***
	(3)	(3)	(3)	(3)
High-rank workers	9***	29***	21***	17***
	(2)	(4)	(3)	(3)
High-rank firms &				
Low-rank workers	-38***	-17***	-29***	-24***
	(5)	(4)	(5)	(4)
High-rank workers	-7***	-6***	-12***	-10***
	(1)	(2)	(2)	(2)
	First-difference of the unemployment rate			
Low-rank firms &				
Low-rank workers	46***	24***	34***	38***
	(8)	(8)	(7)	(7)
High-rank workers	18***	40***	32***	38***
	(5)	(13)	(9)	(7)
High-rank firms &				
Low-rank workers	-76***	-45***	-77***	-50***
	(14)	(9)	(12)	(11)
High-rank workers	-13***	-12***	-19***	-21***
	(4)	(4)	(6)	(5)

Notes: Estimates of net poaching (share of worker-firm 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. To avoid excessive decimal places, the dependent variables range from $[-100, 100]$, while the cyclical indicators range from $[-1, 1]$.

rank workers at low-rank firms increase by 0.24 to 0.46 percentage points. This slowdown of the job ladder is substantially different for high-rank workers. Net poaching of high-rank workers at high-rank firms only declines by 0.12 to 0.21 percentage points, while that of low-rank firms declines by 0.18 to 0.40 percentage points.

Poaching also responds to HP-detrended unemployment. For every additional percentage point between the unemployment rate and its HP trend, the net poaching rate increases by 0.17 to 0.22

percentage points for low-rank firms, and declines by 0.17 to 0.38 for high-rank firms. For high-rank workers, for an additional percentage point between the unemployment rate and its HP trend, the net poaching rate into low-rank firms increases by 0.09 to 0.29 percentage points, while that into high-rank firms declines by 0.06 to 0.12 percentage points. It is worth noting that the slowdown in movement from low-rank to high-rank firms is greater in magnitude for low-rank workers than for high-rank workers. Therefore low-rank workers are especially unlikely to move to high-rank firms during recessions. Overall, this evidence suggests that the countercyclical shift of low-rank workers at low-rank firms is driven by a slowdown in the job ladder. The fact that this slowdown affects both low-rank workers and high-rank worker employment at high-rank firms suggests that workers of all ranks agree on which firms are of relatively desirable workplaces.[34]

These results on the cyclical changes in net poaching and net nonemployment flows for worker-firm rank groups helps illustrate the role of the cyclical job ladder in increasing and decreasing the agreement between worker and firm ranks. In the times of high unemployment that follow recessions, net poaching drives basically all changes in worker-firm rank agreement. During recessions, net nonemployment transitions have some have explanatory effect for changes in employment composition for these worker-firm rank combinations. This is true for high-rank workers at low-rank firms. For high-rank workers, net nonemployment transitions favor high-rank rather than low-rank firms, so this effect offsets the countercyclical change in the poaching margin, which favors low-rank firms. The countercyclical increase in high-rank workers at low-rank firms has an unambiguous interpretation of a sullying effect. The countercyclical decline in low-rank workers at high-rank firms is due to both differential nonemployment hiring as well as poaching, but the poaching margin explains more of this change.[35] The nonemployment differential explains at most 30% for low-rank workers at firms of low- and high-rank is found when we rank workers and firms by their effects from our additive model.[36] Therefore the countercyclical decline in the share of low-rank workers at high-rank firms is mostly due to sullying effects. Most of the countercyclical increase in the agreement between worker rank and firm rank can be attributed to sullying rather than cleansing effects. The cyclical job ladder

[34]This result is consistent with the findings of Haltiwanger, Hyatt, and McEntarfer (2018).

[35]This result suggests that readers should exercise caution in interpreting our finding of an increase in the measured agreement between worker rank and firm rank as itself evidence of a cleansing effect on worker-firm matches. If low-rank workers have higher output at high-rank firms than at low-rank firms, then output can be reduced when low-rank workers are concentrated at low-rank firms.

[36]See the results for the additive model in Tables 6 and 7 where we use the first-difference of the unemployment rate as the cyclical indicator, $(2.01-1.55)/(2.01-1.55+0.34+0.74) \approx 0.30$. Ranking workers by employment duration and firms by their poaching hire share, we obtain the somewhat lower $(2.51-2.19)/(2.51-2.19+0.46+0.76) \approx 0.21$.

Table 8: Relationship between worker-firm correlations and the unemployment rate

	Employment & poaching share	Earnings & productivity	Additive worker & firm effects	Ranked workers & surplus
	Difference in unemployment from its HP trend			
Rank correlation	-0.0	0.3***	0.3	0.3***
	(0.2)	(0.1)	(0.2)	(0.1)
	First-difference of the unemployment rate			
Rank correlation	1.2**	0.5***	1.7***	-0.4
	(0.5)	(0.1)	(0.4)	(0.3)

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. To avoid excessive decimal places, the dependent variables range from $[-100, 100]$, while the cyclical indicators range from $[-1, 1]$.

drives changes in the agreement of worker ranks and job ranks.

3.3.3 Worker-firm rank correlation and unemployment

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.[37] Regression evidence is shown in Table 8. Specifically, we allow workers and firms to be in one of 50 employment-weighted rank bins, and we measure the correlation between worker rank and firm rank for those bins. This correlation, which is in the interval $[-1, 1]$, is calculated separately for each quarter in the data, and serves as the dependent variable for regressions on our two cyclical indicators.[38] While there are differences across ranking methods, overall the measured correlation between worker rank and firm rank increases in labor market downturns. For example, a one percentage point increase in the unemployment rate is associated with an increase of 0.012 in the correlation between a worker's rank measured by employment duration and a firm's rank from the poaching hire share. This relationship is stronger for the first-difference of the unemployment rate, which suggests that the correlation between worker ranks and firm ranks increases during recessions more than in the times of high unemployment that follow them.

To interpret the results of Table 8, it is important to consider the results on the changes in the

[37]For the correlations and a discussion, see Appendix C.3 and Appendix Table C3.

[38]Note that to avoid excess decimal places in Table 8, we multiply the correlations by 100.

employment of different worker-firm rank combinations that we discuss in Section 3.3.1. Countercyclical changes in the degree of agreement between worker rank and firm rank are driven by several mechanisms, some of which strengthen and others of which weaken this relationship. Our results show that, overall, positive sorting tends to strengthen during labor market downturns.

3.4 Summary of empirical findings

Our empirical evidence shows how labor market composition and sorting change with aggregate conditions. All four of our ranking methods deliver similar results. During recessions, the employment share of low-rank workers declines, while that of high-rank workers increases. This change can be attributed to the differential net nonemployment transitions of low- vs. high-rank workers. Although workers of all ranks are less likely to work during economic downturns, low-rank workers are especially unlikely to work. Thus worker composition can be characterized by a countercyclcial cleansing effect: relatively unproductive workers leave employment during downturns.

Cyclical changes in firm composition are quite different. During economic downturns, the employment share of low-rank firms increases. This is true whether we rank firms by poaching hire share, labor productivity, or transformations of worker earnings. This increase in the employment share of low-rank firms is driven by the countercyclical decline in net poaching from low-rank to high-rank firms. During expansions, high-rank firms poach workers away from low-rank firms as workers move up the job ladder. But during downturns, the job ladder shuts down, and employment increases for low-ranked firms.

This countercyclcial cleansing of the worker distribution and sullying of the firm distribution drive changes in labor market sorting. As low-rank firms and high-rank workers have an increasing share of employment during labor market downturns, the share of such job matches naturally increases. This weakens the degree of sorting and is driven by a sullying effect. We also find that low-rank workers are less likely to work at high-rank firms, which strengthens sorting. This change can mostly be attributed to the slowdown of the job ladder and hence also appears to be a sullying effect. The decline of low-rank workers at high-rank firms dominates, and the measured agreement between worker rank and firm rank increases during recessions.

4 A Model of heterogeneous workers and firms

In this section, we use a model of labor market sorting to interpret the facts documented in Section 3, focusing on the cyclical changes in worker and firm composition. Specifically, we seek to understand the mechanisms that may drive countercyclial shifts in employment toward high-rank workers and low-rank firms. Such effects matter for sorting becuase these composition changes drive the observed changes in the worker-firm rank distribution. Before describing the details of the model it is useful to discuss the intuition.

First, consider the worker distribution. The worker distribution will be cleansed in downturns if the marginal matches tend to be those with low type workers. To take an extreme case, if match output is almost entirely a function of worker type then in a recession the dissolved matches will be almost entirely those with low type workers, as opposed to low type firms. Then the question becomes whether a such a worker-centric production function is consistent with sullying of the firm distribution in recessions. We argue that it is, and that it is driven by on-the-job search. Moscarini and Postel-Vinay (2013) have shown that the sullying of the firm distribution is consistent with a model where there are heterogeneous firms and on-the-job search.[39] In their model, lower recruiting during a recession leads to fewer poaching losses for low type firms, allowing them to grow relative to high type firms. This poaching mechanism can operate under any amount of firm heterogeneity. Thus it is consistent with a match output function that is mostly (though not completely) a function of worker type. We show that model estimation implies a production function that is driven by worker type.

But will the sullying effect dominate the firm distribution? In order to do so, this sullying effect of recessions must overcome the cleansing effect. In the models of Barlevy (2002) and Moscarini and Postel-Vinay (2013), on-the-job search is the mechanism for the sullying effect of recessions. During labor market downturns, the quit rate is lower, and so workers spend more time in lower-value matches. However, if a match has a value that is too low, then it may not be able to offer compensation to the worker that provides more value than unemployment. A decrease in such relatively unproductive job matches is the cleansing effect of recessions. In the framework that follows, either the cleansing or sullying effect can dominate the firm distribution.

[39] Cairó, Hyatt, and Zhao (2018) also show that this mechanism can operate in a simplified version of Lise and Robin (2017) that abstracts from worker heterogeneity and only considers firm heterogeneity.

4.1 Model environment

We work with the model proposed by Lise and Robin (2017). Their model includes aggregate shocks, worker heterogeneity, firm heterogeneity, and on-the-job search. Despite its richness, the model can be solved relatively easily via the simulated method of moments. We briefly describe the main features here, see Lise and Robin (2017) for details.

Time is discrete and goes on forever. There is a fixed mass of workers. Workers are indexed by $x \in [0,1]$. Firms (jobs) are indexed by $y \in [0,1]$.[40] Jobs may be vacant or filled. Maintaining a vacant job costs $c(v(y))$, which is exogenous to the firm. When matched with a worker, a job produces flow output $f(x,y,z)$ per period, where z is the productivity shock. Workers search while unemployed, and search with a lower intensity s while matched. Search is random, and the number of meetings is determined by a Cobb-Douglas meeting function that takes searching workers and vacancies as its inputs. 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. The timing is as follows. At the beginning of each period z changes from z_{t-1} to z_t. Next, exogenous separations occur at rate δ. Endogenous separations also occur, dissolving matches with negative expected surplus. Then, given the aggregate state, firms decide how many vacancies to post. Unemployed and employed workers meet vacancies according to an aggregate meeting function. When a worker and firm meet they decide whether to match and at what wage. Finally, production takes place and wages are paid.

A key feature of the Lise and Robin (2017) model is wage setting. Wages are renegotiated only when one party can credibly threaten to dissolve the match if the wage goes unchanged. This may occur if the aggregate state changes, changing match production and/or the outside options. It may also occur if the worker receives a job offer from another firm. When a firm meets an unemployed worker, the firm makes a take it or leave it offer of an initial wage. The worker must accept the offer or refuse and remain unemployed. In equilibrium the firm will offer a wage that delivers nothing more

[40]Note that there is a distinction between a worker or firm's type, and the rank a worker or firm will receive from a ranking method, as argued by Eeckhout and Kircher (2011). Papers such as Hagedorn, Law, and Manovskii (2017) propose methods of recovering worker and firm types via a ranking method, but except in specific model environments there is not a one-to-one correspondence between observable (estimated) rankings and unobservable worker and firm types.

than the worker's reservation value, and the firm will extract all the expected surplus of the match.[41] 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.[42]

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

$$S(x,y,z_t) = f(x,y,z_t) - b(x,z_t) + \frac{1-\delta}{1+r}\mathbb{E}_t\left[\max\left\{S(x,y,z_{t+1}),0\right\}\right] \tag{2}$$

where $\frac{1}{1+r}$ is the discount factor. In this expression $f(x,y,z_t) - b(x,z_t)$ is the single period flow surplus of the match. It consists of match output, less the value the worker would derive from unemployment $b(x,z_t)$. 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 (2) is taken over future values of z_{t+1}. If the surplus is still positive in $t+1$ the match is still profitable, and yields the continuation value $S(x,y,z_{t+1})$. If the surplus of the match would become negative ($S(x,y,z_{t+1}) < 0$) then the match is dissolved and the continuation value is zero.

It is remarkable that the surplus depends only on z_t and not, e.g., the distribution of workers across firms and unemployment. As Lise and Robin (2017) explain, the split of the surplus will of course depend on distributions, but the total surplus need not. Their wage setting mechanism ensures that surplus is preserved under employer-to-employer 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

[41] This is a major difference between the model of Lise and Robin (2017) and that of Hagedorn, Law, and Manovskii (2017). In the latter model, workers exiting nonemployment obtain the full surplus of the job match. While this feature allows Hagedorn, Law, and Manovskii (2017) to rank workers by the wages that they are paid, introducing this into the Lise and Robin (2017) model would make aggregate uncertainty considerably less tractible. More generally, the second-price auction wage setting mechanism of Lise and Robin (2017) often yields a negative relationship between wages and worker productivity for nonemployment exiters, see Bagger and Lentz (2019). Ranking workers by nonemployment duration and firms by their poaching hire rank allows us to avoid this issue.

[42] 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.

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. The reader is referred to Lise and Robin (2017) for further derivations.

4.2 Estimation

4.2.1 Data moments

Lise and Robin (2017) estimate their model via the simulated method of moments (SMM), targeting 28 moments related to unemployment, vacancy posting, job flows, value added, and dispersion. Importantly, all of their moments can be constructed from publicly available data. However, the restriction to public use data means there are not direct measures of worker types, firm types, and the joint match distribution. Instead, Lise and Robin (2017), roughly speaking, use duration dependence in unemployment to pin down the worker type distribution, the cross-sectional dispersion of value added to pin down the firm type dispersion, and time-series correlations in these objects to infer the production function and matching behavior. The LEHD data we analyze above provides more direct measures of worker and firm composition over the business cycle. In the SMM objective function, we replace some of the Lise and Robin (2017) heterogeneity moments with our own LEHD-derived moments.[43]

For the purposes of estimation we rank workers by nonemployment duration and firms by poaching hire shares, since these map most cleanly into the model framework and are also cheap to calculate on the model-simulated data. Construction of the model-implied moments is hampered by the computational cost of simulating a large panel of workers and firms on every iteration of the SMM solver. In the Lise and Robin (2017) model all workers of a given type have the same expected unemployment duration, and all firms of a given type have the same expected poaching share. We can group the "true" worker and firm types into (population weighted) terciles based on these expected values.

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

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

divide worker types into terciles, based on average shares of employment, just as in the data. Similarly, 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 1 of Tables 1 and 3. We substitute these new moments into the 28 used by Lise and Robin (2017), and do not target related moments on unemployment duration and productivity dispersion. We put a high subjective weight on the LEHD moments to be sure that they are influential in the estimation.

4.2.2 Parameterization

We parameterize the model in the same way as Lise and Robin (2017). The production function has 6 free parameters p_1 to p_6:

$$p(x,y,z) = z(p_1 + p_2 x + p_3 y + p_4 x^2 + p_5 y^2 + p_6 xy). \tag{3}$$

The aggregate meeting function is Cobb-Douglas and transforms searching workers L_t and vacancies V_t into meetings according to $m(L_t,V_t) = \alpha L_t^{0.5} V_t^{0.5}$, with elastcitiy 0.5 and efficiency α is to be estimated. The convex vacancy posting cost function is $(1+c_1)^{-1} c_0 v^{1+c_1}$, where c_0 and c_1 are estimated. Exogenous job destruction δ and the relative intensity 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. The flow utility of unemployment b for each is set to provide 70% of output from a worker's most productive match at aggregate state $z = 1$. 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.

4.3 Results

4.3.1 Parameter estimates

Table 9 shows our parameter estimates, alongside those of Lise and Robin (2017). For the most part the estimates are qualitatively similar to each other: the parameters for employed worker search effort s, vacancy posting costs c_0 and c_1, the exogenous job destruction rate δ, and the aggregate state ρ and σ are nearly identical. Estimated matching efficiency is somewhat different, increasing from 0.497 in Lise and Robin (2017) to 0.680. The shape parameters of the Beta distribution for workers, β_1

Table 9: Parameter estimates

Parameter	Lise & Robin (2017) estimation	LEHD moments estimation
α	0.497	0.668
s	0.027	0.026
c_0	0.028	0.030
c_1	0.084	0.080
δ	0.013	0.011
σ	0.071	0.073
ρ	0.9997	0.9997
β_1	2.148	2.577
β_2	12.001	11.270
p_1	0.003	0.003
p_2	2.053	1.998
p_3	-0.140	-0.186
p_4	8.035	8.017
p_5	-1.907	-1.744
p_6	6.596	6.517

and β_2 are closer to each other when we target LEHD moments, which indicates a more symmetric distribution. The parameters for the production function itself exhibit relatively little change.

Table 10 shows how the two estimated economies behave with respect to the Lise and Robin (2017) targeted moments. The targeted, simulated moments are generally close to each other (and the data), as would be expected when the estimated parameters are similar. There are some noteworthy differences among untargeted moments. When we target LEHD moments, we do not target the moments for particular unemployment durations. First, in our LEHD moments estimation, unemployment is a more persistent state than implied by the unemployment duration moments targeted by Lise and Robin (2017). Furthermore, we do not target the standard deviation of labor productivity or its evolution over time. We obtain a much higher standard deviation of labor productivity of 0.758 than the 0.494 implied by the data.[44]

Table 10 also shows the LEHD moments. Each β is the coefficient from a regression of a worker tercile or firm tercile share of employment on the first difference of unemployment. For example, β_L^{worker} is the coefficient for the employment share of low type workers. The cyclical composition moments are taken from column 1 of Tables 1 and 3. The second column is the same quantities,

[44]We note that Lise and Robin (2017) obtain this labor productivity dispersion moment using Compustat data from Bloom et al. (2018). Compustat firms are larger and more stable than the typical business, see Davis et al. (2007). There is therefore reason to interpret the data moment on labor productivity as a lower bound.

Table 10: Moments: data & model-implied

Moment	Data	Lise & Robin (2017) estimation	LEHD moments estimation
		Moments from Lise and Robin (2017)	
$\mathbb{E}[U]$	0.058	0.059	0.060
$\mathbb{E}\left[U^{5p}\right]$	0.035	0.032	*0.047*
$\mathbb{E}\left[U^{15p}\right]$	0.018	0.018	*0.041*
$\mathbb{E}\left[U^{27p}\right]$	0.010	0.011	*0.039*
$\mathbb{E}[UE]$	0.421	0.468	0.231
$\mathbb{E}[EU]$	0.025	0.028	0.015
$\mathbb{E}[EE]$	0.025	0.025	0.036
$\mathbb{E}[V/U]$	0.634	0.744	1.003
$\mathbb{E}$[sd labor prod]	0.494	0.505	*0.758*
sd$[V]$	0.206	0.105	0.089
sd$[VA]$	0.033	0.034	0.033
autocorr$[VA]$	0.932	0.991	0.992
corr$[V,U]$	-0.846	-0.975	-0.680
corr$[U,VA]$	-0.860	-0.983	-0.979
sd$[U]$	0.191	0.203	0.150
sd$\left[U^{5p}\right]$	0.281	0.315	*0.152*
sd$\left[U^{15p}\right]$	0.395	0.413	*0.145*
sd$\left[U^{27p}\right]$	0.478	0.439	*0.141*
sd$[UE]$	0.127	0.127	0.047
sd$[EU]$	0.100	0.095	0.159
sd$[EE]$	0.095	0.112	0.186
sd$[V/U]$	0.381	0.306	0.220
sd[sd labor prod]	0.039	0.038	*0.036*
corr$[V,VA]$	0.721	0.996	0.749
corr$[UE,VA]$	0.878	0.978	0.166
corr$[EU,VA]$	-0.716	-0.910	-0.946
corr$[UE,EE]$	0.695	0.977	-0.169
corr[sd labor prod, VA]	-0.366	-0.361	*-0.458*
		LEHD Moments	
β_L^{worker}	-44.9	*-53.6*	-34.3
β_H^{worker}	31.6	*26.8*	17.6
β_L^{firm}	12.0	*-1079.6*	31.0
β_H^{firm}	-8.9	*348.6*	-59.1

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

calculated from simulated data using the moments from Lise and Robin (2017). The implied moments from our estimation are in the third column of Table 10. On the worker side, the model consistently matches the empirical pattern that the worker distribution shifts away from low-rank workers and toward high-rank workers. Specifically, for every one percentage point increase in the unemployment rate, the Lise and Robin (2017) parameter estimates predict a decline in the employment share of low-rank workers of 0.536 percentage points and an increase in that of high-rank workers by 0.268 percentage points. These are very close to what we obtain from the LEHD data, which show a decline of 0.449 percentage points in the employment share of low-rank workers and an increase of 0.268 percentage points for high-rank workers. Our own estimates that target the worker and firm composition moments from LEHD data do no better: they show a decline of 0.343 percentage points in the employment share of low-rank firms and an increase of 0.176 percentage points in the employment share of high-rank workers.

On the firm side, in the estimation in Lise and Robin (2017), the employment share of low-rank firms decreases, while that of high-rank firms increases. Specifically, a one percentage point increase in the unemployment rate is associated with a 10.796 percentage point decrease in the employment share of low-rank firms, and a 3.486 percentage point increase in the employment share of high-rank firms. This contrasts with the increase in the employment share of low-rank firms of 0.120 percentage points, and decline in that of high-rank firms of 0.089 percentage points. Thus, the Lise and Robin (2017) framework does not automatically generate our finding regarding cyclical changes in firm composition: cleansing effects dominate, and strongly so. However, when we target the cyclical firm and worker moments from LEHD data, we obtain something closer to what the data describe: and increase of 0.310 percentage points in the employment share of low-rank firms and a 0.591 percentage point decline in the employment share of high-rank firms. The Lise and Robin (2017) framework therefore has the potential to demonstrate cleansing of the worker distribution and sullying of the firm distribution.

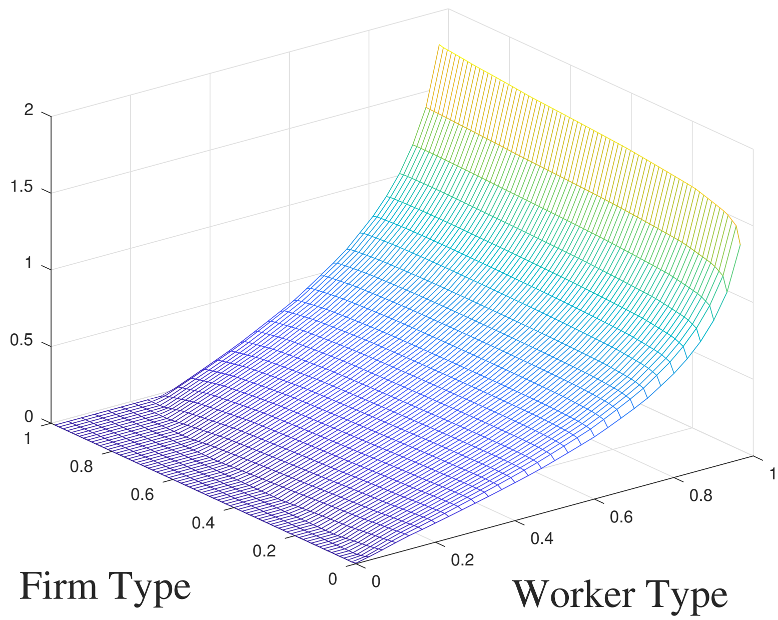
4.3.2 What drives labor market composition and sorting?

We have shown that the Lise and Robin (2017) can produce a countercyclical increase in the share of firms with a high poaching rank. This quantitative exercise provides guidance on the mechanisms that generate cyclical changes in labor market composition and sorting that we observe in Section 3.

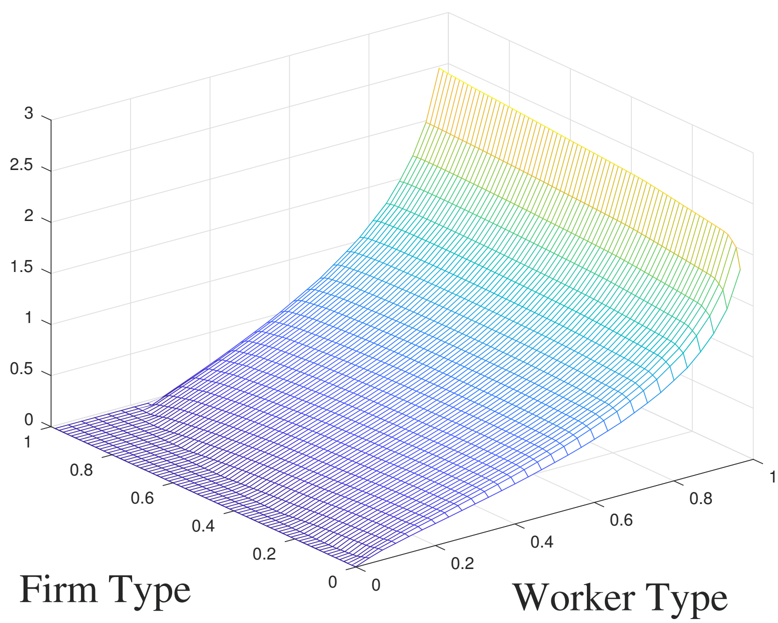
First, workers rather than firms must drive the match value of output. Figure 3 shows the estimated production functions. The Lise and Robin (2017) model estimates distribution of worker types, and given the parameters the masses of each type of firm are endogenous. Thus, to compare the production

Figure 3: Model implied production functions

(a) Lise & Robin (2017) parameter estimates

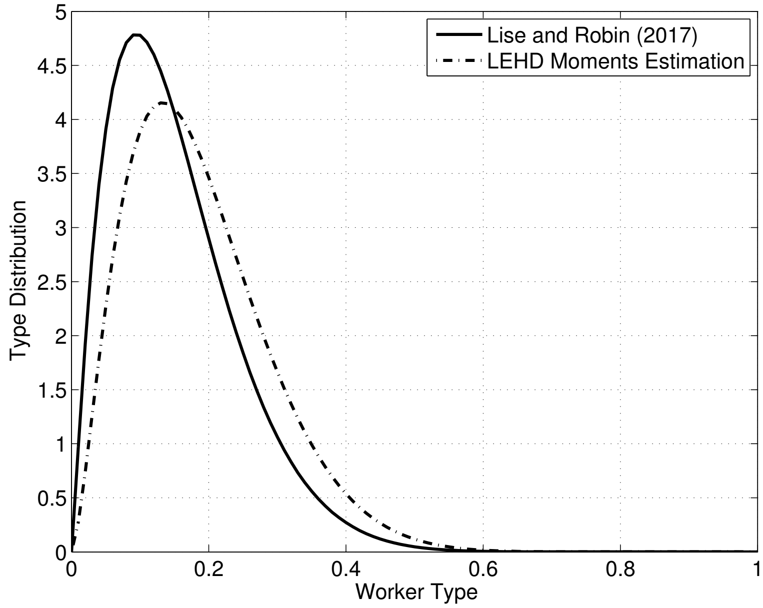


(b) Parameter estimates targeting LEHD moments



Notes:Worker and firm type distribution normalized to uniform.

Figure 4: Worker distributions



functions from two equilibria we need to normalize the worker and firm distributions. In Figure 3 the production functions are normalized so that each increment along the worker (firm) type axis covers an equal fraction of the worker (firm) distribution. Put differently, the worker and firm populations have been reindexed to be uniform distributions. It is apparent that both production functions put more weight on the worker type, and are nearly flat in firm type.[45] A large empirical literature indicates that workers, rather than firms, drive the match value of output. Our results here are consistent with this finding. Abowd, Kramarz, and Margolis (1999) reported that workers, rather than firms, explained most of the variation in wages in their early analysis of linked employer-employee data, and most studies that followed have confirmed this.

We show the shift in the worker type distribution in Figure 4. This shows that, after targeting the LEHD moments, the worker distribution targets higher ranked workers. In order to understand the mechanics of sorting in the Lise and Robin (2017) model, it is helpful to keep in mind that a worker's

[45]Our worker ranking methods, additionally, provide a method of confirming this empirical finding. Specifically, the worker and firm ranking method of Hagedorn, Law, and Manovskii (2017) provides estimates of the surplus from different worker-firm matches. Inverting the surplus function, we can recover the implied match value of worker-firm output (see Appendix E for a more detailed description of the inversion method). The results of this exercise are shown in Appendix Figure E1. The results are qualitatively similar to those from Lise and Robin (2017). Workers drive the match value of output, and there is an inflection among relatively high-type workers. This exercise therefore also suggests there are relatively large changes in output by worker type at the upper end than for middle-type workers.

optimal match is determined by the production function. Taking the first derivative of the production function with respect to firm type y yields

$$\frac{\partial}{\partial y}(p_1 + p_2 x + p_3 y + p_4 x^2 + p_5 y^2 + p_6 xy) = p_3 + 2p_5 y + p_6 x.$$

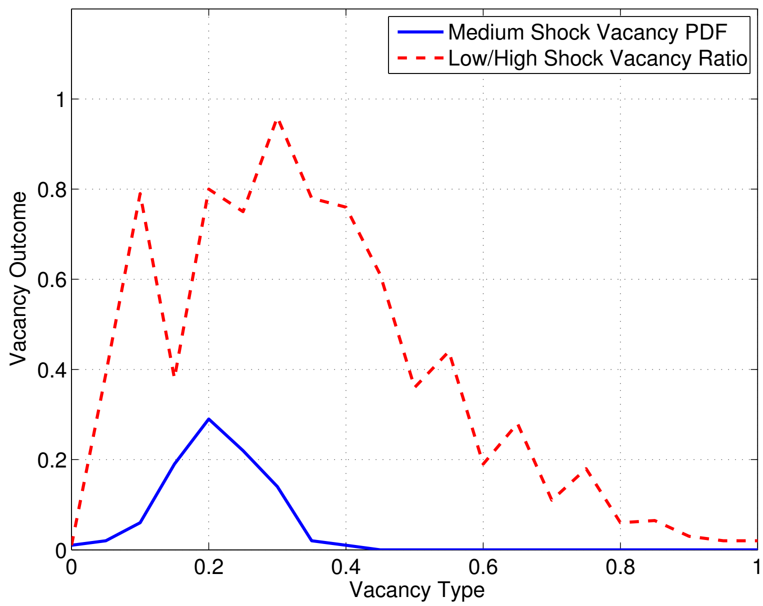
There are two regions in which monotonicity prevails. At the lower extreme workers for whom $x \leq p_3/p_6$ strictly prefer firms with a lower value of y and so monotonically move toward firms with $y = 0$. This occurs at value 0.021 in Lise and Robin (2017) and value 0.029 when we target the LEHD moments. Likewise, there is a region where workers monotonically move toward firms with rank $y = 1$, for workers with value $x \geq (p_3 + 2p_5)/p_6$. This occurs at value 0.60 in Lise and Robin (2017) and 0.56 when we target LEHD moments. For the region in between these values of x, the optimal firm is of type $y = (p_6 x - p_3)/(2p_5)$. Workers will gradually move toward these optimal matches as they move up the ladder. Figure 4 shows that the share of workers in either region characterized by monotonicity is small in both Lise and Robin (2017) and when we target our LEHD moments.

Another feature of the LEHD moments estimation is that firm entry and exit decisions should not shift materially by job ladder rank over the business cycle. Countercyclical "cleansing" of the firm distribution is a feature of the baseline Lise and Robin (2017) model when we do not target our cyclical share moments as shown in Table 10. However, our cyclical share moments suggest that there is more, not less, employment at low-rank firms when unemployment is high. The framework of Moscarini and Postel-Vinay (2013) abstracts from the cleansing margin of recessions, and is able to generate countercyclical increases in employment at low-rank firms. In order to match our cyclical moments, the model's implied production function and worker type distribution lead to less cyclicality in the share of vacancies by firms of different types.

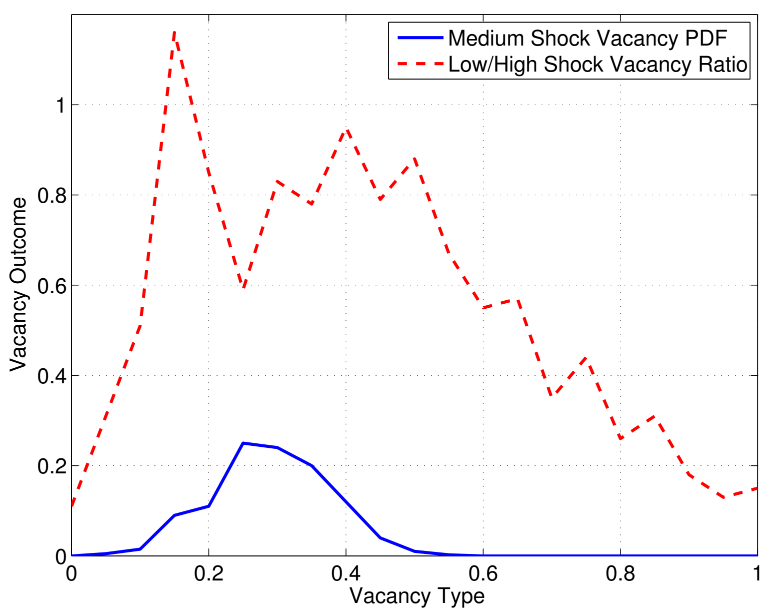
The lower tail of the firm type distribution can be characterized in in Figure 5, which contains the distribution of vacancies that prevail in the long run under a zero shock (50th percentile), as well as the relative changes for low (25th percentile) vs. high (75th percentile) aggregate states of the economy. This exercise is done both for the baseline Lise and Robin (2017) parameter estimates, as well as parameter estimates that target the new cyclical moments estimated on LEHD data. Note that in both cases, the firm rank is not to be confused with the value of the match. The highest value matches (i.e., those that imply the highest surplus) are found in the middle of the firm rank distribution, somewhere between 0.2 and 0.3 in both versions of the estimation. Targeting the LEHD moments changes the

Figure 5: Model implications for the cyclical distribution of vacancy posting

(a) Lise and Robin (2017) estimation



(b) LEHD moment estimation



Notes: Vacancy posting distribution using Table 9 parameter estimates.

baseline distribution of vacancies: in Panel 5(a), there is a much more pronounced left tail of low ranked firms, whereas in Panel 5(b) this panel is less pronounced.

Figure 5 also provides insights into the nature of countercyclical "cleansing" of low-rank firms. This can be seen in the measures of the low vs. high shock ratio of vacancies. Naturally, there are fewer vacancies with the aggregate state is low relative to when it is high, hence the ratio of vacancies is generally less than one. At the extremes of the distribution, firms post less than 20% of the vacancies in the low state than they do in the aggregate state, however, Figure 6 also illustrates that there are approximately zero firms operating in this range of the distribution. The ratio of vacancies in the low vs. high state is also not monotonic, and what is especially interesting is a spike in the ratio of vacancies that occurs at the gridpoint in which the distribution of vacancies loses most of its mass. In other words, there is extra activity at the bottom of the job ladder: the set of firms that, when there is a high aggregate state, has an almost trivial mass since an offer to an employed worker has an approximately 100% chance of them being poached away. Note that this spike is apparent in the baseline estimates of Lise and Robin (2017).[46] However, when we we target the LEHD moments this spike in vacancy posting at the bottom of the firm type distribution is much more dramatic. That it exceeds one at this marginal case after targeting LEHD moments implies that some of the lowest-ranked firms are posting *more* vacancies in worse states of the economy than in better ones.

These results haves implications for how the low end of the wage offer distribution is determined. There are competing forces at work in the Lise and Robin (2017) model. First, there is the "cleansing" effect of recessions as in Caballero and Hammour (1994): when firms have relatively low value from producing, they are more likely to sensitive to macroeconomic shocks. This means that low aggregate states of the economy will drive low valued firms out of the distribution, including those at the lower end. The competing effect is described by Moscarini and Postel-Vinay (2013): the lowest ranked firms will obtain more value from posting a vacancy when they can hold on to their workers for longer. This mechanism can induce very low value firms to post relatively more vacancies. The latter mechanism can generate a spike in the vacancy posting distribution at its lowest end. When we match the countercyclical increase in the employment share of low rank firms we observed in our linked employer-employee data, this sullying effect dominates.

[46]This nonmonotonicity is less apparent in Lise and Robin (2017), Figure 3, Panel A, when they present similar results for a larger difference in aggregate states.

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 linked 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-rank 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 evidence 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 have presented evidence of countercyclical increases in positive sorting. These changes in labor market sorting naturally follow from changes in worker and firm composition. During labor market downturns, low-rank workers are less likely to work at high-rank firms, strengthening the agreement between worker ranks and job ranks. At the same time, high-rank workers are more likely to work at low-rank firms during labor market downturns, weakening sorting. These changes is are mostly due to the slowdown in the job ladder. The job ladder slows down more for low-rank workers than for high-rank workers. Thus the countercyclical decline of low-rank workers at high-rank firms is greater than the increase of high-rank workers at low-rank firms. Thus the degree of agreement between worker rank and firm rank increases during recessions.

We evaluate our findings in the context of the model of cyclcial labor market sorting proposed by Lise and Robin (2017). This framework delivers countercyclical cleansing of the worker distribution that is very similar to what we find in our linked employer-employee data. In contrast, in order to obtain a countercyclical increase in low-rank firms, we must target this directly when we estimate the Lise and Robin (2017) model. Doing so highlights the importance of workers driving the match value of output. Our results also illustrate that the sullying effect of recessions must be especially pronounced if it is to overcome its cleansing effect.

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Appendices

A Employment and transition definitions

We use 11 states of LEHD microdata that have data available for 1994-2014.[47] Our definitions follow the notation established by Abowd et al. (2009), augmented to include employer-to-employer transitions 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:

[47] 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, seven transition concepts: four for employer-to-employer transitions, two for transitions into and from nonemployment, and an exhaustive residual for those with dominant employers, job stayers.

In addition to these, we create an additional nonemployment hire measure that is useful when calculating a firm’s rank when hiring from poaching. This measure excludes recalls

$$
ne2\_norecall_{ikt} = \begin{cases} 1, & \text{if } domb_{ikt+1} = 1 \\ & \text{and } domb_{ilt} \neq 1 \forall l \\ & \text{and } domb_{imt-1} \neq 1 \forall m \\ & \text{and } domb_{ikt-2} \neq 1 \\ 0, & \text{otherwise.} \end{cases}
$$

A.3 Aggregation

We consider the evolution of total consecutive quarter employment. For workers in group i and firms in group j, this is expressed as:

$$E_{ijt} = \sum_{ij} b_{ijt+1}.$$

Total employment evolves via poaching hires and hires from nonemployment. Total poaching hires for workers in group i and firms in group k are:

$$P^a_{ikt} = \sum_{ik} (wq_{ijkt} + aq_{ijkt}).$$

Total poaching separations for workers of group i from firms of group j are

$$P^s_{ijt} = \sum_{ij} (wq_{ijkt} + aq_{ijkt-1}).$$

Total nonemployment hires for workers of group i into firms of group k are

$$N^a_{ikt} = \sum_{ik} en2\_doma2_{ikt}.$$

Total nonemployment separations for workers of group i from firms of group j are

$$N^s_{ijt} = \sum_{ij} en2\_doms2_{ijt}.$$

B Worker ranking implementation details

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

B.1 Method 1: worker nonemployment duration and firm poaching hire share

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.1.1 Ranking firms by poaching share of hires

In a manner similar to Bagger and Lentz (2019), 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 or from non-employment for each firm in the 11 states of the LEHD microdata. We include as employer-to-employer transitions hires both same-quarter wq_{ijkt} and adjacent-quarter aq_{ijkt} transitions. A same-quarter transition occurs if the worker has positive earnings from both the previous and the new employer in the transition quarter. An adjacent-quarter 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 nonemployment hires, we exclude all one-quarter recall hires, and so we use $ne2\_norecall_{ikt}$. 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 the poaching share of hires for firm k as the ratio of hires from other employers to total hires, as follows:

$$\frac{\sum_k wq_{ijkt} + aq_{ijkt}}{\sum_k ne2\_norecall_{ikt}}.$$

Firms are then rank ordered into 50 bins according to their poaching share.

B.1.2 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.2 Method 2: average earnings and labor productivity

B.2.1 Ranking workers based on average earnings

In our fourth method, we rank workers in a way that is motivated by the fact that high type workers may exhibit higher average earnings. We simply rank workers by the average of their residual earnings after controlling for age and time-period fixed effects. Note that this is the initial guess of a worker's rank in our additive model (Method 3) and our reranking workers and surplus approach (Method 4).

B.2.2 Ranking firms based on revenue productivity

We use revenue data from the U.S. Census Bureau's Business Register to measure labor productivity, i.e., revenue-per-worker. We use all available revenue data from 1994-2014.[48] 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.

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.

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

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

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

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

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

B.3 Method 3: additive worker and firm effects

We estimate worker and firm fixed effects via an iterative algorithm that follows Guimarães and Portugal (2010). We fit the following model for earnings outcomes

$$W = B\xi + D\theta + F\psi$$

where W is the $N \times 1$ dimensional vector total earnings observations w_{ijt}, B is an $N \times G_B$ dimensional matrix of birth cohort by time fixed effects, D is an $N \times G_D$ dimensional matrix of person-specific fixed effects, and F is an $N \times G_F$ dimensional matrix of firm effects. Our goal is to recover the $1 \times G_B$ dimensional vector ξ of fixed effects for birth cohort c at time t ξ_{ct}, the $1 \times G_D$ dimensional vector θ of person-specific fixed effects, and the $1 \times G_F$ dimensional vector ψ of firm-specific fixed effects.

We can express the least-squares formula for this problem in terms of a cross-product matrix similar to Abowd, Kramarz, and Margolis (1999):

$$\begin{bmatrix} B'B & B'D & B'F \\ D'B & D'D & D'F \\ F'B & F'D & F'F \end{bmatrix} \begin{bmatrix} \xi \\ \theta \\ \psi \end{bmatrix} = \begin{bmatrix} B'W \\ D'W \\ F'W \end{bmatrix}$$

which, after rearranging terms, can be expressed as

$$\begin{bmatrix} B'B\xi + B'D\theta + B'F\psi = B'W \\ D'B\xi + D'D\theta + D'F\psi = D'W \\ F'B\xi + F'D\theta + F'F\psi = F'W \end{bmatrix}.$$

which is a system of three equations. Solving each of these independently yields

$$\begin{bmatrix} \xi = (B'B)^{-1}B'(W - D\theta - F\psi) \\ \theta = (D'D)^{-1}D'(W - B\xi - F\psi) \\ \psi = (F'F)^{-1}F'(W - B\xi + D\theta) \end{bmatrix}.$$

We iterate between these sets of equations to obtain the least squares solution. In fact, solving each of these equations can be done using group means since all of our independent variables are dummy variables. As the datasets we use in this analysis contains billions of person-quarter observations (e.g. 50 million workers times twenty quarters implies one billion person-quarter observations), omitting computational matrix inversion allows us to greatly speed up our computation time. To see how we can skip having a computer run a tediously slow regression program on our massive dataset, note that the first equation of our system specifies a separate indicator for each birth cohort c at each quarter in time,

$$\xi_{ct} = \frac{1}{\sum_{ij} \mathbb{1}(w_{ijct} > 0)} \sum_{ij} (w_{ijct} - \theta_i' d_i - \psi_j' f_j)$$

and for each worker i,

$$\theta_i = \frac{1}{\sum_{jct} \mathbb{1}(w_{ijct} > 0)} \sum_{jct} (w_{ijct} - \xi_{cb} b_{cb} - \psi_j' f_j)$$

and for each firm j,

$$\psi_j = \frac{1}{\sum_{ict} \mathbb{1}(w_{ijct} > 0)} \sum_{ict} (w_{ijct} - \xi_i' b_i - \theta_i' d_i).$$

In other words, these are the least squares solutions to a high-dimensional set of mutually exclusive indicator variables. The least squares solutions are sample means of residuals, which can be calculated directly without having a computer multiply or invert matrices.

We can now solve for θ_i, ψ_j, and ξ_{ct} for the universe of our 11 states of linked employer-employee data. We first compute the average log earnings of each birth cohort by time cell $\widehat{\xi}_{ct} = \Sigma_{ij} w_{ijct}$ of each worker, this is our initial guess of the birth cohort by time effect. We then proceed as follows.

1. Estimate the initial worker effects $\widehat{\theta}_i = w_{ijt} - \widehat{\xi}_{ct}$.

2. Estimate the intial firm effects $\widehat{\psi}_j = w_{ijt} - \widehat{\xi}_{ct} \widehat{\theta}_i$.

3. Update the birth cohort by time effects $\widehat{\xi}_{ct} = w_{ijt} - \widehat{\theta}_i - \widehat{\psi}_j$,

4. Update the worker effects $\widehat{\theta}_i = w_{ijt} - \widehat{\psi}_j - \widehat{\xi}_{ct}$.

5. Update the firm effects $\widehat{\psi}_j = w_{ijt} - \widehat{\theta}_i - \widehat{\xi}_{ct}$.

6. Proceed back to step 3 until 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.4 Method 4: worker reranking and surplus

We implement an algorithm for ranking workers and firms that borrows heavily from Hagedorn, Law, and Manovskii (2017). It is substantially simplified and was not intended to be a direct replication of this method.

B.4.1 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.4.2 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.4.3 Surplus-based firm ranking

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

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

1. Compute the following four firm-specific variables:
   - $N(j)$: The number of workers hired from nonemployment by firm j

- $p(\hat{x}, j)$: The number of workers of estimated type $\hat{x}$ hired from 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:

$$\pi(\hat{x}, j) = \frac{u(\hat{x})\mathbb{1}\left[p(\hat{x}, j) > 0\right]}{\sum_{\hat{x}} u(\hat{x})\mathbb{1}\left[p(\hat{x}, j) > 0\right]} \tag{4}$$

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

$$F\left(p(\hat{x}, j), \pi(\hat{x}, j), N(j)\right) = \sum_{i=0}^{p(\hat{x}, j)} \left(\begin{array}{c} N(j) \\ i \end{array} \right) \pi(\hat{x}, j)^{i} \left(1 - \pi(\hat{x}, j)\right)^{N(j)-i} \tag{5}$$

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

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

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

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

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

1. Construct the set $J(\hat{x})$ which consists of all firms j that hire any worker of type $\hat{x}$ from nonemployment.

2. For each firm $j \in J(\hat{x})$, compute $\bar{w}(\hat{x}, j)$, the average wage paid by firm j to workers of type $\hat{x}$ hired from nonemployment.

3. We define the reservation wage for type $\hat{x}$, $w^r(\hat{x})$, is the 10th percentile of the set of $w(\hat{x}, j)$ where $j \in J(\hat{x})$. Note that Hagedorn, Law, and Manovskii (2017) propose using the minimum average wage as the reservation wage, but we find that this is a very noisy signal, whereas the 10th percentile is smoothly increasing in worker type.

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

$$\Omega^u(j) = \sum_{\hat{x} \text{ s.t. } \hat{\mathbb{B}}(\hat{x},j)=1} \frac{\frac{u(\hat{x})}{U}\left(\bar{w}(\hat{x}, j) - w^r(\hat{x})\right)}{\sum_{\hat{x} \text{ s.t. } \hat{\mathbb{B}}(\hat{x},j)=1} \frac{u(\hat{x})}{U}} \tag{6}$$

The job filling rate for firm j is a function of the probability that the firm encounters an unemployed worker, $\mathbb{M}_v$, times the probability that the worker's type, $x(i)$, matches the firm's set of acceptable worker types ($\hat{\mathbb{B}}(\hat{x}(i), j) = 1$). 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:

$$\tilde{q}^u(j) = \sum_{\hat{x} \text{ s.t. } \hat{\mathbb{B}}(\hat{x},j)=1} \frac{u(\hat{x})}{U} \tag{7}$$

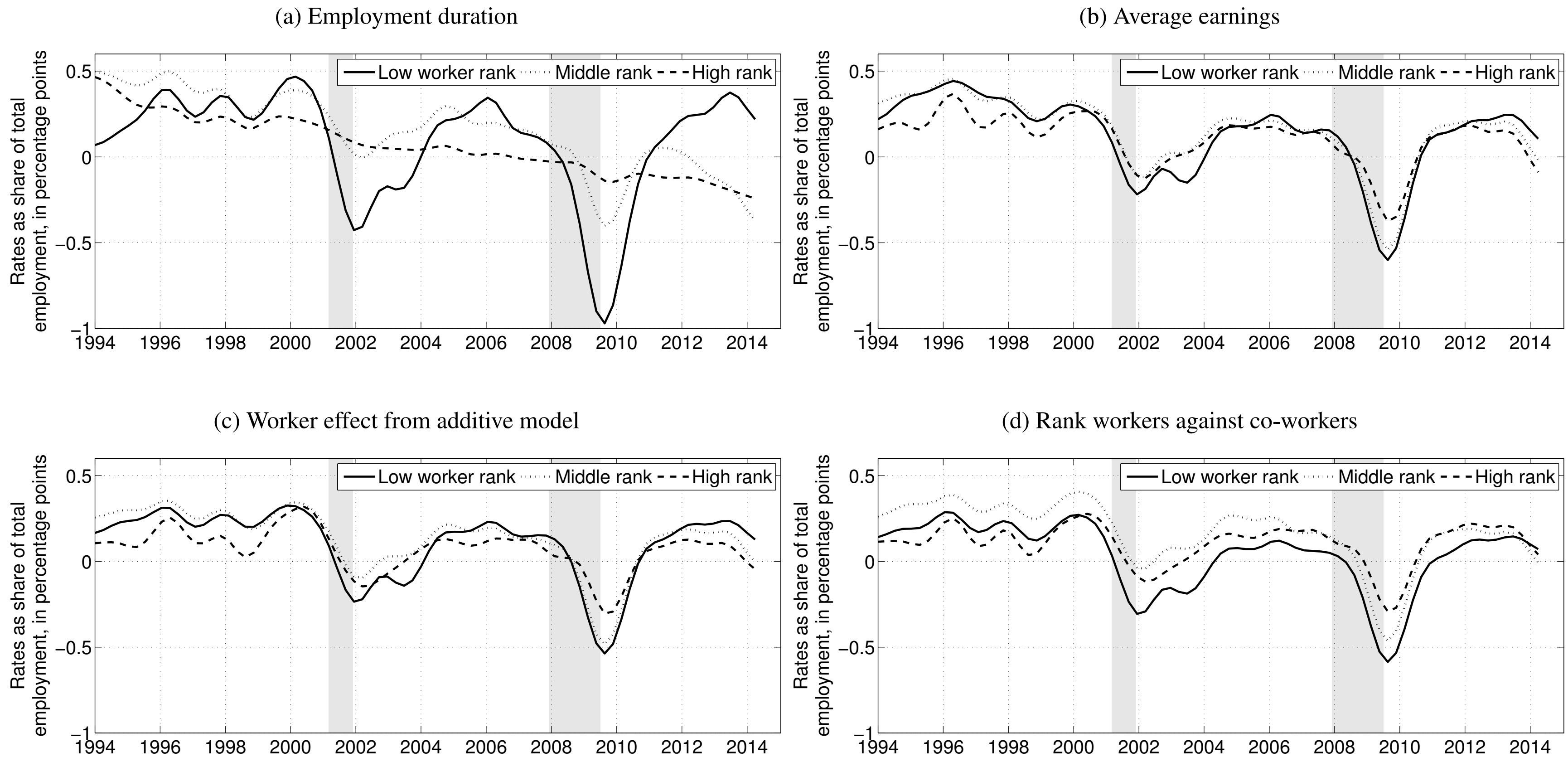
C Supplemental tables and figures

C.1 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.We show these transition rates in Figure C1. Figure C1 shows net hires from nonemployment by worker type. Net employment growth declines sharply during recessions for all three types of workers. The 2007-2009 recession has more of a decline in employment than the 2001 recession. However, for high productivity workers, especially in the 2007-2009 recession, their employment did not decline nearly as much as it did for the lower productivity groups. When considering the employment transitions across firms of different types, it is helpful to keep in mind the findings of Haltiwanger et al. (2018) that firms that are higher-ranked in the job ladder are net poachers, and that low-rank firms rely disproportionately on nonemployment to obtain their workers. Figure C2 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 C3 shows net poaching by firm type. Note that net poaching for each worker type is equal to zero by construction (each employer-to-employer transition contributes exactly one poaching gain and one poaching loss). Low type firms lose workers via poaching flows, and high type firms gain workers throughout the time period, but this movement away from low type firms and toward high type firms slows substantially during recessions.

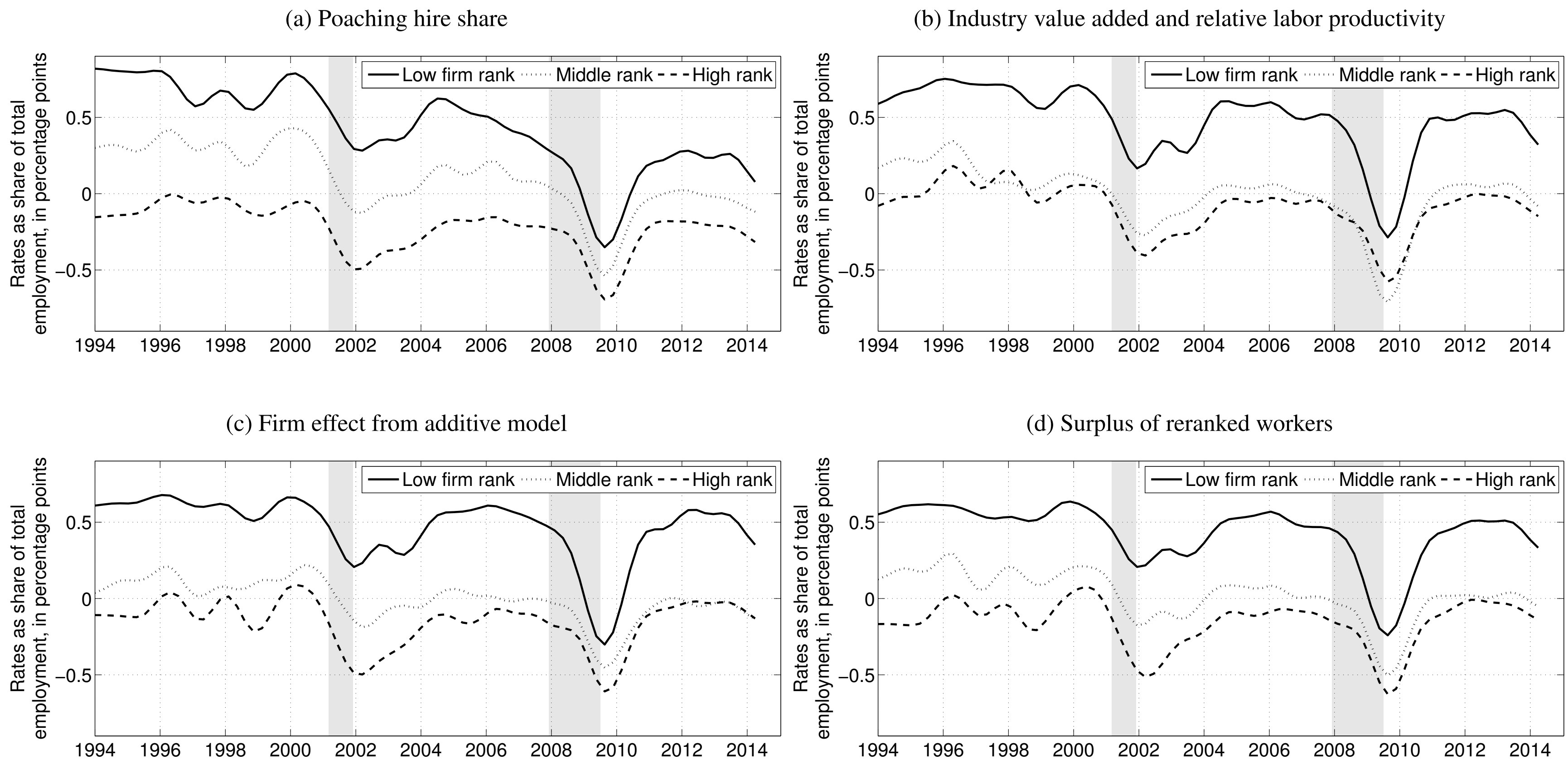
Figures C1, C2, and C3 help illustrate how the employment composition effect led to a larger build-up at low-rank firms in the wake of the 2001 recession than the 2007-2009 recession. Following Haltiwanger et al. (2018), in order to see a counter-cyclical build-up at the low-end of the job ladder, the “poaching margin” must overwhelm the “nonemployment margin.” In other words, the counter-cyclical decline in the movement of workers from low-rank firms to high-rank firms must be larger than the decline in nonemployment for low-rank firms. In the wake of the 2001 recession, there was relatively little change in the difference in nonemployment hiring for high- vs. low-rank firms and so the change in poaching dominages. However, in the 2007-2009 recession the excess nonemployment hiring by low-rank firms shut down, mitigating the build-up in the share of employment at low-rank firms.

Figure C1: Percent change in worker employment



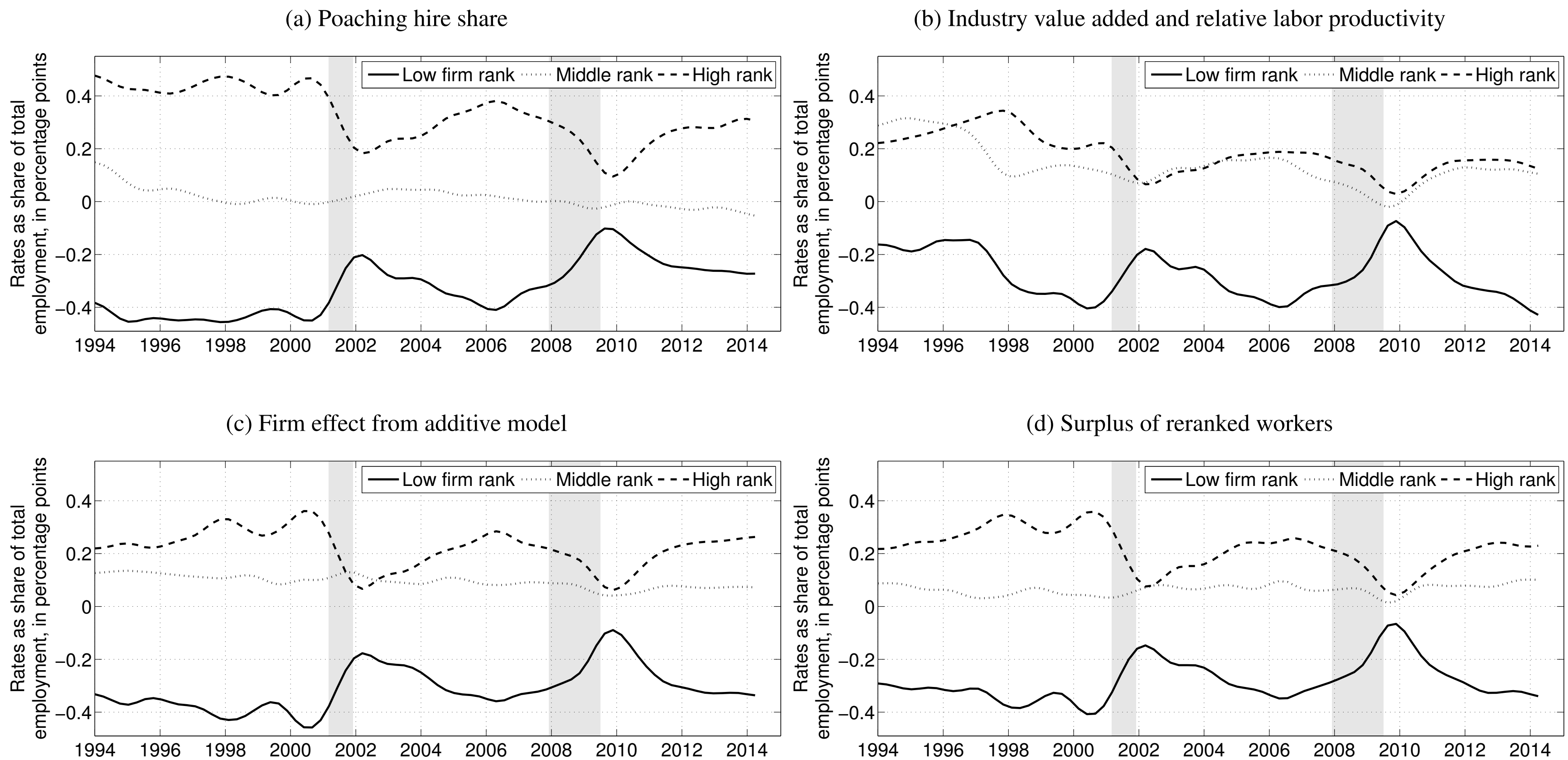
Notes: Shaded regions indicate recessions. Data seasonally adjusted and Henderson-filtered using X-11.

Figure C2: Percent change in firm employment: Nonemployment



Notes: Shaded regions indicate recessions. Data seasonally-adjusted and Henderson-filtered using X-11.

Figure C3: Percent change in firm employment: poaching



Notes: Shaded regions indicate recessions. Data seasonally adjusted and Henderson-filtered using X-11.

C.2 Worker-Firm Rank Shares

Now, we turn from composition to sorting. Figures C4, C5, and C6 show how worker sorting evolves over this time period. 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 e.g. the share of low-rank workers in all three firm categories sum to the share of low-rank workers C4.[49] The upward movement in the share of workers at low-rank firms, which occurs throughout the 2001 and 2007-2009 recessions, is accounted for early on by a decline in the share of low ranked workers at low- and middle-ranked firms, but, in the late stages

[49]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.

Table C1: Change in share and unemployment (HP)

	Nonemployment & poaching share	Earnings & productivity	Additive worker & firm effects	Ranked workers & surplus
		Low-rank firms		
Low-rank workers	-0.7	0.4	0.9	1.1
	(1.3)	(1.0)	(1.0)	(0.7)
Mid-rank workers	4.4***	2.9***	2.7***	2.4***
	(0.9)	(0.5)	(0.5)	(0.7)
High-rank workers	2.6***	1.8***	2.0***	1.8***
	(0.9)	(0.5)	(0.5)	(0.5)
		Middle-rank firms		
Low-rank workers	-3.9***	-1.4	-1.4**	-0.8
	(1.1)	(0.8)	(0.5)	(0.6)
Mid-rank workers	1.6**	-0.3	0.8	0.9*
	(0.7)	(0.7)	(0.6)	(0.5)
High-rank workers	2.9***	0.8	1.6**	1.7***
	(0.8)	(0.6)	(0.7)	(0.5)
		High-rank firms		
Low-rank workers	-6.6***	-2.0***	-2.7***	-3.0***
	(1.3)	(0.5)	(0.7)	(0.7)
Mid-rank workers	-2.2***	-1.7***	-2.7***	-2.8***
	(0.7)	(0.4)	(0.6)	(0.6)
High-rank workers	1.9**	-0.5	-1.2	-1.3*
	(0.8)	(1.0)	(1.0)	(0.7)

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.

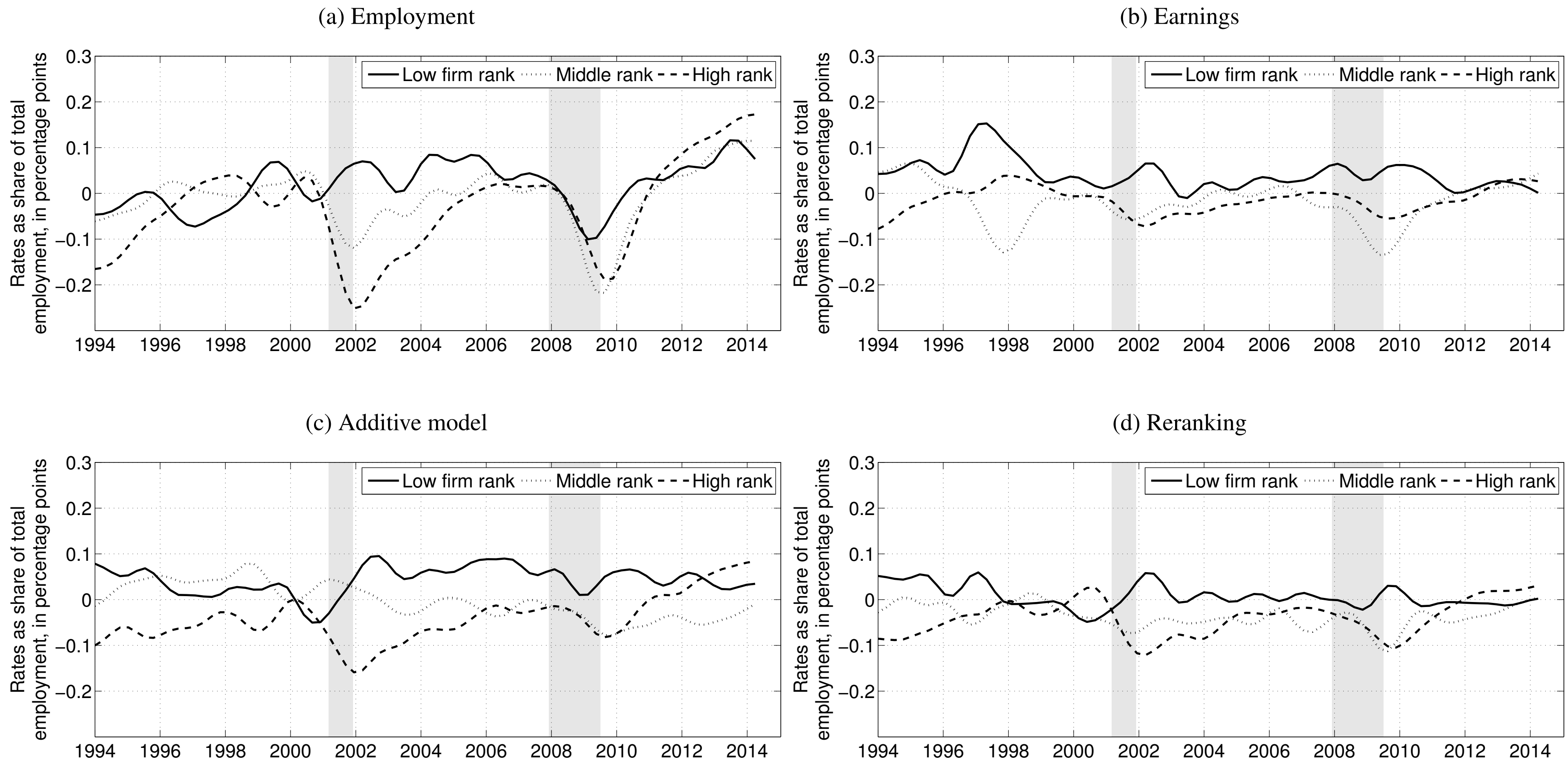
of as well as after recessions, the share of low productivity workers at high ranked firms declines by more than the middle and high ranked firms. Workers of all types, but particularly middle and high productivity workers, are more likely to work at low productivity firms during and immediately after recessions. This movement of higher-type workers into low-type firms more than offsets the decline in employment of low type workers at low type firms at the outset of each of the two recessions, and so the employment share at low-type firms exhibits countercyclical increases. These cyclical changes are shown in Tables C1 and C2.

Table C2: Change in share and unemployment (FD)

	Nonemployment & poaching share	Earnings & productivity	Additive worker & firm effects	Ranked workers & surplus
		Low-rank firms		
Low-rank workers	-0.8	0.9	-8.3***	0.5
	(2.3)	(1.7)	(3.0)	(2.4)
Mid-rank workers	0.5	3.5*	10.4***	4.2***
	(1.5)	(1.8)	(2.3)	(1.4)
High-rank workers	2.3*	4.6***	9.8***	3.5**
	(1.3)	(1.3)	(1.9)	(1.3)
		Middle-rank firms		
Low-rank workers	-2.7*	-5.9***	-18.6***	-10.3***
	(1.4)	(1.2)	(2.0)	(1.7)
Mid-rank workers	2.4*	-0.7	4.7***	-6.1***
	(1.4)	(1.3)	(1.7)	(1.4)
High-rank workers	6.8***	4.2***	10.8***	2.8**
	(1.7)	(1.2)	(1.8)	(1.3)
		High-rank firms		
Low-rank workers	-9.1***	-6.5***	-18.1***	-4.1***
	(1.6)	(1.7)	(3.1)	(1.3)
Mid-rank workers	-5.1***	-4.2***	-1.8	-1.1
	(1.6)	(1.5)	(1.7)	(1.2)
High-rank workers	5.7**	4.1**	11.0***	10.6***
	(2.3)	(1.7)	(1.6)	(2.2)

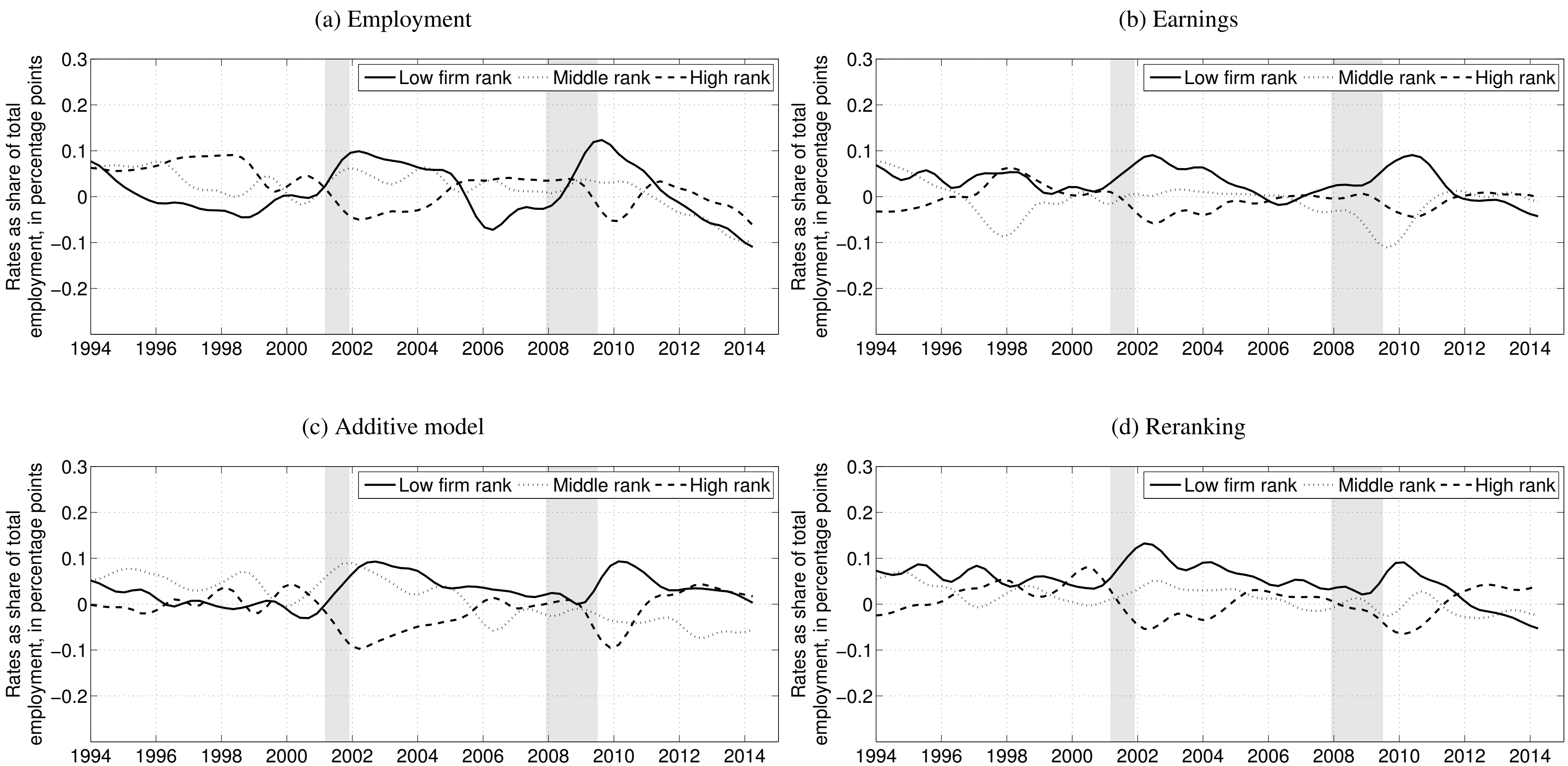
Notes: Estimates of change in share of employment on the seasonally-adjusted unemployment rate, season dummies, and a time trend. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively. Standard errors are in parentheses.

Figure C4: Change in worker and firm share combinatons by tercile: low-rank workers



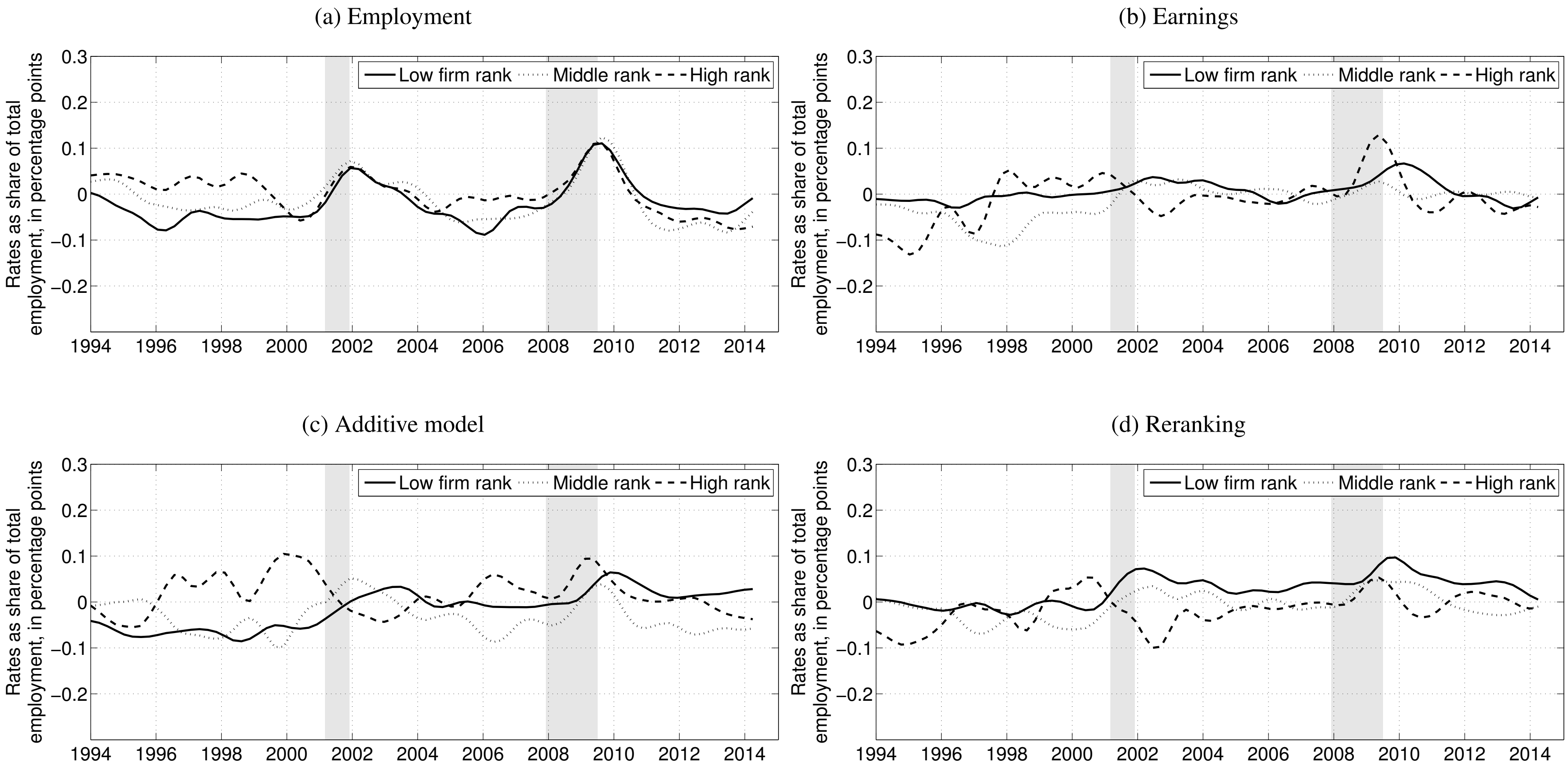
Notes: Shaded regions indicate recessions. Data seasonally adjusted and Henderson-filtered using X-11.

Figure C5: Change in worker and firm share combinations by tercile: middle-rank workers



Notes: Shaded regions indicate recessions. Data seasonally adjusted and Henderson-filtered using X-11.

Figure C6: Change in worker and firm share combinations by tercile: high-rank workers



Notes: Shaded regions indicate recessions. Data seasonally adjusted and Henderson-filtered using X-11.

C.3 Correlations among worker and firm ranks

We measure the correlation between worker ranks and firm ranks from each of the four methods, and present these correlations in Table C3. 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 low- vs. high-rank workers are employed at low- vs. high-rank firms. The revenue productivity method produces the strongest correlation, at 0.35, while the poaching share and employment duration model produces the lowest correlation, at 0.22. The reranking and reservation wage method yields a correaltion of 0.24, and our additive worker and firm effects method yields a correlation of 0.33.

The correlation between worker effects and firm effects in the additive model is larger than some early implementations of Abowd, Kramarz, and Margolis (1999) estimators on linked employer-employee data, which suggested that the correlation between worker type and firm type was close to zero. Our estimates are of the same order of magnitude but smaller than the recently proposed estimator of Bonhomme, Lamadon, and Manresa (2018), and much smaller than that of Borovičková and Shimer (2018). We view our relatively large correlation as the effect of having a very large number of workers and firms, a relatively lengthy panel, and using quarterly rather than annual data. Using annual data for the U.S. in a similar time period, Lamadon, Mogstad, and Setzler report a correlation of 0.10 from estimation that follows Abowd, Kramarz, and Margolis (1999). These reduce the amount of "limited mobility bias" that can drive correlation estimates based on the additive model to zero, see Andrews et al. (2012). We show in Table C4 that implementing our additive estimator on subsets of the data yields much smaller correlations between worker type and firm type. Comparing the correlations across columns also yields information about the relative effects of different commonly used sample selection techniques on worker-firm rank agreement in an additive framework.

Table C3: Correlation of worker and firm ranks across methods

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

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

Table C4: Correlation of additive model worker and firm ranks across implementation methods

Correlation	0.332	0.326	0.165	0.158	0.176	0.172	0.176	0.161	0.173	0.180	0.188
Control Variables											
Age quadratic and time FE	-	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Birth year * time FE	Y	-	-	-	-	-	-	-	-	-	
Random sample											
10%	-	-	-	Y	Y	-	-	-	-	-	-
100%	Y	Y	Y	-	-	Y	Y	Y	Y	Y	Y
Outliers											
20+ Quarters	-	Y	-	-	-	-	-	-	-	-	-
Time range											
1994-2003	-	-	Y	Y	-	-	Y	-	-	-	-
2004-2014	-	-	-	-	Y	-	-	-	-	-	-
1994-2014	Y	Y	-	-	-	-	-	-	-	-	-
2004-2013	-	-	-	-	Y	-	-	Y	-	-	-
1994-2013	-	-	-	-	-	Y	-	-	Y	Y	Y
Frequency											
Quarterly	Y	Y	Y	Y	Y	-	-	-	-	-	-
Annual	-	-	-	-	-	Y	Y	Y	Y	Y	Y
Earnings threshold											
$15,000 2014 dollars	-	-	-	-	-	-	-	-	Y	Y	-
Age restriction											
25 to 55	-	-	-	-	-	-	-	-	-	Y	-
Firm size restriction											
20+ workers	-	-	-	-	-	-	-	-	-	-	Y

Notes: All correlations are statistically distinct from zero at the 0.0001 significance level. Annual estimates end in 2013 because 2014 is only partially available.

D Ranking workers and firms in Lise and Robin (2017)

We assess the Lise and Robin (2017) model in light of our evidence on cyclical labor market sorting. We here explore how to interpret ranking workers by their nonemployment duration and firms by their poaching hire shares in this framework.

D.1 Ranking workers by nonemployment duration

In the Lise and Robin (2017) model, workers search from both unemployment and employment. Matches dissolve both because of exogenous shocks expressed by δ as well as voluntary separations because matches provide negative surplus. We can express the evolution of the unemployment rate according to

$$\begin{aligned} \frac{u_{t+1}(x)}{L_{t+1}} = & \frac{u_t(x)}{L_t}[1 - \int \lambda_t \frac{v_t(y)}{V_t} \mathbb{1}\{S_t(x,y) \geq 0\} dy] + \delta(1 - \frac{u_t(x)}{L_t}) + \\ & \int h_t(x,y)(1 - \mathbb{1}\{(S_{t+1}(x,y) \geq 0\}) dy \end{aligned}$$

where $v_t(y)$ is the total number of vacancies posted by firms of type y in time t, the total number of vacancies posted by firms of all types is V_t, and $h_t(x,y)$ is the total share of type x workers employed at type y firms at time t. This equation expresses that there are three mechanisms through which the unemployment rate changes from one period to the next. Some workers will receive job offers that offer nonnegative surplus $S_t(x,y) \geq 0$ and therefore offer at least as much value as unemployment unemployment. Employed workers can be hit by the exogenous separation shock δ and move to unemployment from this mechanism. Third, some share of matches can be dissolved because in the new aggregate state they provide negative surplus.

This formulation of the share of workers of a given type x is helpful to provide guidance on how to interpret workers ranked by their employment duration. Employment durations are increasing in the number of matches that provide nonnegative surplus $S(x,y) \geq 0$ to a worker. Workers who are willing to accept jobs from a larger set of firms will exit unemployment more rapidly. Workers who are more frequently employed at jobs that provide marginal surplus and are therefore at risk of the new draw of the aggregate state z inducing $S_{t+1} < 0$ are also more likely to be employed. Ranking workers by their employment duration therefore reflects the compatibility of workers with the labor market, the number of jobs that exist that such workers can fill. Note that it is necessarily the case that it returns the most productive workers. In the parameterization of Lise and Robin (2017), as well as in our LEHD moments estimation, the output is strictly increasing in worker type x for firms of type y. However, the flow utility of unemployment also increases in a worker's type, and so only workers toward the middle of the worker type distribution are willing to accept jobs from firms of any type in sufficiently good states of the economy.[50] The highest-ranked workers therefore have the interpretation of being the workers that are most compatible with the firms that operate in the economy.

D.2 Ranking firms by poaching hire share

We now discuss the interpretation of the Bagger and Lentz (2019) poaching hire share in the context of the Lise and Robin (2017) model. Bagger and Lentz (2019) define the poaching share as the fraction of hires that come from other firms, as a fraction of total hires. In Lise and Robin (2017), this rate can be expressed as

$$\pi(y) = \frac{\int\int sh(x,y')\mathbb{1}[S(x,y,z) > S(x,y',z)]dxdy'}{\int \frac{u_t(x)}{L_t}\mathbb{1}(S(x,y,z) > 0)dx + \int\int sh(x,y')\mathbb{1}[S(x,y,z) > S(x,y',z)]dxdy'}$$

where L_t is the total number of workers in the the economy. This rate counts the total number of accepted offers to employed workers, as a share of total nonemployment and employment hires. Note that a relatively high surplus value $S(x,y,z)$ will increase both the numerator and the denominator, as poaching an employed worker from a firm of type y' implies $S(x,y,z) > S(x,y',z) > 0$.

[50] See Figure 4 of Lise and Robin (2017).

E Reranking production function inversion estimation

To estimate the production implied from the reranking methodology of identifying worker and firm types, we employ the job surplus inversion method described in Hagedorn, Law, and Manovskii (2017). The production function is a function of the surplus, $S(\hat{x},\hat{y})$, generated by the matching of a worker of type $\hat{x}$ with a firm of type $\hat{y}$ plus the value of a vacancy to a firm of type $\hat{y}$, $V_v(\hat{y})$ and the value of unemployment to a worker of type $\hat{x}$, $V_u(\hat{x})$. These factors are weighted by the time-discount factor (β) and the job destruction rate (δ). Specifically, the productivity of a specific worker-firm match, $f(\hat{x},\hat{y})$ is:

$$f(\hat{x},\hat{y}) = (1-\beta(1-\delta))\,S(\hat{x},\hat{y}) + (1-\beta)V_v(\hat{y}) + (1-\beta)V_u(\hat{x}) \tag{8}$$

E.1 Value of unemployment by worker type

We estimate the value of unemployment, $V_u(\hat{x})$, by estimated worker type, $\hat{x}$, as the present discounted value of the minimum quarterly earnings from nonemployment accepted by workers of type $\hat{x}$ from any firm type. For every worker-firm type combination, we calculate $e^{10p}(\hat{x},\hat{y})$, the 10th percentile of residual earnings (after controlling for age). The value of unemployment to a specific worker type $\hat{x}$ is the minimum of the e^{10p} across all potential firm-types given the worker type.

$$V_u(\hat{x}) = \frac{1}{1-\beta}\min_{\hat{y}} e^{10p}(\hat{x},\hat{y}) \tag{9}$$

E.2 Value of employment by worker-firm combination

We estimate the value to a worker of being employed by worker-firm type combination $V_e(\hat{x},\hat{y})$ as the average across all observed jobs spells of the present discounted value of earnings of workers of type $\hat{x}$ over the job spells at firms of type $\hat{y}$. If $i(\hat{x},\hat{y})$ is an index of job spells of type $\hat{x}$ workers at type $\hat{y}$ firms and d_i is the duration of job spell i then $V_e(\hat{x},\hat{y})$ is:

$$V_e(\hat{x},\hat{y}) = \sum_{i(\hat{x},\hat{y})} \frac{1}{N_i} \sum_{t=0}^{d_i-1} \beta^t e_{it} + \beta^d V_u(\hat{x}) \tag{10}$$

E.3 Match surplus by worker-firm combination

We estimate the worker-firm type combination match surplus, $S(\hat{x},\hat{y})$, as the scaled difference between the value of a worker's value of being employed at a firm of a given type and the worker's value of employment, where the scaling factor is the measure of worker's bargaining power α. More specifically,

$$S(\hat{x},\hat{y}) = \frac{V_e(\hat{x},\hat{y}) - V_u(\hat{x})}{\alpha} \tag{11}$$

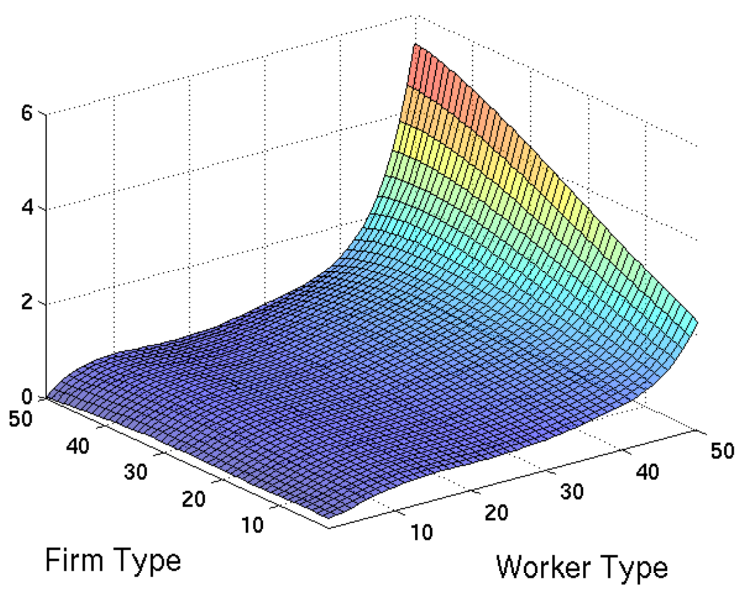
We use $\alpha = 0.5$, as in the model of Shimer and Smith (2000).

E.4 Vacancy value by firm type

We estimate the vacancy value to a firm of type $\hat{y}$, $V_v(\hat{y})$. The vacancy value is a function of the discount factor β, the worker's bargaining power α, the job destruction rate δ, and the average firm surplus for firms of type $\hat{y}$, $\Omega(\hat{y})$. The firm surplus is estimated using the surplus-based ranking method described in Appendix Section B.4.3.

$$V_v(\hat{y}) = \frac{\beta}{1-\beta}\frac{1-\alpha}{\alpha}(1-\delta)\Omega(\hat{y}) \tag{12}$$

Figure E1: Production Function from Worker Reranking & Surplus Method



Notes:Worker and firm type distribution normalized to uniforms.