Firm Market Power, Worker Mobility, and Wages in the US Labor Market*

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Abstract

Worker mobility and wages, relative to productivity, have declined in the US amid a rise in employer market power. I propose a theory of the labor market linking these trends, in which a decline in employer competition, characterized by a lower number of firms per worker, drives the decline in worker mobility and wages. The model has two main ingredients: first, there exists a finite number of employers that differ in productivity, and second, employers exert market power by excluding their offers from the set of outside options faced by their employees. The combined effect of these features, in response to a decreasing number of firms per worker, is to reduce the value of workers' outside options, thereby reducing wages and worker mobility in equilibrium. Overall, the calibrated model accounts for 2/3rd of the decline in employer-to-employer transitions rate and a fifth of the decline in wages relative to productivity from the 1980s to the 2010s. I evaluate the model's key predictions using the public-use data from the Census and document that labor markets characterized by a lower number of firms per worker are associated with reduced measures of worker mobility and average wages.

JEL Classification: E2, J3, J6, J42

Keywords: Labor Market Power, On the Job Search, Finite Firms, Poaching, Job Flows, Wages

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1 Introduction

Recent studies have documented a secular rise in employer market power in the US economy.[1] This increase is often viewed in light of concurrent long-run changes in labor market outcomes, such as an overall stagnancy of median wages and declining labor share of income.[2] I examine the link between employer market power and wages by exploring another macroeconomic aggregate that has declined in recent decades: job-to-job transitions.[3] Using a random-search model of the labor market, I document that an increase in employer market power, characterized by a declining number of firms per worker in the labor market, reduces the outside options of employed workers. This, in turn, has a wage-suppressing effect and reduces workers' opportunities to quit for better offers. Overall, the model predicts that a declining number of firms per worker in the relevant labor market of workers is associated with a slowing in wages and a decline in job-to-job flows. Figure 1 shows that the decreasing trends in wages relative to productivity and job-to-job transitions rate have occurred concurrently with the long-run decline in firms per worker in the US economy.

The theoretical predictions of the model can be seen in light of a recent empirical finding that aggregate real wages of the US economy covary much more strongly with the job-finding rate of the *employed*, rather than the *unemployed*, both of which act as a channel for transmission of labor demand (Moscarini & Postel-Vinay 2017, Karahan, Michaels, Pugsley, Şahin & Schuh 2017). The job-finding rate of the employed, which manifests in the pace of job-to-job transitions, reflects how intensely firms compete for employed workers. In this setting, the rising market power of firms translates to less competition among employers. Evidence of this has been documented in the form of lower outside offers for workers in more concentrated labor markets (Caldwell & Danieli 2022, Schubert, Stansbury & Taska 2022) and increasing instances of anti-competitive practices, such as non-compete covenants and no-poaching agreements, being enforced by firms (Krueger & Ashenfelter 2018, Starr, Bishara & Prescott 2020). Both forces can potentially restrict the scope of labor reallocation to more productive, higher-paying jobs over the job ladder, thereby reducing average wages in the economy. This raises the question: can existing models of the labor market, with on-the-job search linking job-to-job flows to average

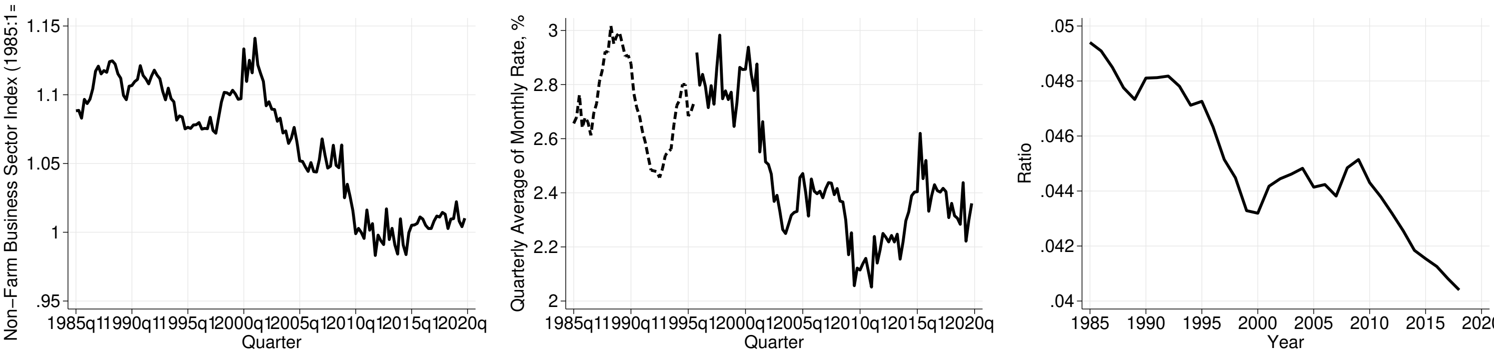
[1]See Manning (2021) for a comprehensive review of the current state of the literature.

[2]See, for example, Autor, Dorn, Katz, Patterson & Van Reenen (2020), and De Loecker, Eeckhout & Unger (2020) documenting an increase in product and employer market power and exploring its implications on declining labor share.

[3]See evidence of a long-run decline in labor market dynamism, and particularly job-to-job flows starting from the late 1990s in Hyatt & Spletzer (2016), Molloy, Trezzi, Smith & Wozniak (2016), Fujita, Moscarini & Postel-Vinay (2022).

Figure 1: Worker Mobility, Wages and Firms Per Worker, 1985-2019

(a) Wages/Productivity (b) EE rate, % (c) Employer Firms Per Employed Worker



Notes: Bureau of Labor Statistics, Current Population Survey, and Business Dynamics Statistics, 1985-2019. Firms per worker are the ratio of annual stocks of the number of firms and employees. Post-1995 Employer-to-employer transitions rates are quarterly averages of monthly flows from Fujita, Moscarini & Postel-Vinay (2022) who use the Current Population Survey and correct for missing observations after a survey methodology change in 2007. Pre-1995 Employer-to-employer transitions rates are quarterly flows expressed as monthly rates (Diamond & Şahin 2016). Wages are expressed as a quarterly index of hourly compensation deflated by the implicit price deflator. Labor productivity is a quarterly index of output per hour deflated by the implicit price deflator. Wages and productivity are measured for the non-farm business sector.

wages in equilibrium, explain the aggregate decline in the two outcomes resulting from decreasing competition among firms for workers?

I address this question by building a tractable model of the labor market that accounts for the effect of firm market power on inter-firm competition, equilibrium worker mobility, and wage behavior. In the model, unemployed and employed workers sample jobs from firms that are heterogeneous in productivity. On-the-job search prompts firms to compete with one another for employed workers, resulting in poaching behavior and an endogenous job ladder. As workers climb the job ladder, they sort themselves into more productive firms, deriving higher value from successive employment matches. Wages are determined by the sequential auctions framework of Cahuc, Postel-Vinay & Robin (2006), where employed workers trigger competition between their current and poaching employers. This results in a wage that is determined by workers' outside offers and the joint value of the employment match. A more lucrative outside offer grants the worker more leverage in the wage negotiation process, resulting in the worker getting a higher share − and the firm a lower share − of the joint match value.

The pace at which workers climb the job ladder and match with more productive firms is a function of search frictions and firm competition in the labor market. The latter is governed by two ingredients: First, the model assumes a finite set of firms instead of a continuum of atomistic firms. This results in a discrete job offer distribution, with each firm having a non-zero vacancy share. Thus, decreasing the number of firms in the economy increases their vacancy share, thereby granting them more weight in the offer distribution of job seekers. Second, employer firms exclude their offers from the outside options of their employees, similar in spirit to Jarosch, Nimczik & Sorkin (2021). In other words, when an employed worker contacts an outside firm, she prompts the incumbent and poaching employers to compete for her. This results in the worker and the potentially winning employer negotiating a wage that is a function of the foregone offer made by the losing employer, or in other words, the worker's outside option. A high offer made by the losing firm gives the worker more leverage in the bargain and forces the winning firm to match the higher value. However, the forgone outside offer contains the value from the option of searching on-the-job and matching with the firm that wins the worker. This means the winning firm competes with its own future offer in the continuation value of the worker's outside option. Removing such an offer reduces the outside option of the worker, consequently putting downward pressure on the negotiated wage and giving the winning firm more leverage in the bargain.

The model is calibrated to fit key moments of the 1985-90 US labor market. As part of the calibration, I show that the model can reproduce empirically observed labor market flows, including job-to-job transitions and those into and out of employment, as well as measures of wage dispersion and wage growth of job stayers in the economy. I then undertake the key counterfactual exercise: I vary the number of firms in the economy and find that job-to-job flows, average wages (normalized by productivity), and workers' values derived in the model increase with the level of firm competition in the economy. Further, as more firms crowd the market, employers compete more intensely to retain workers, leading to an increase in the wage growth of job stayers. At the same time, workers are more likely to reach the upper limit of their maximum wage before making a job switch, leading to a fall in the wage growth of job switchers.

I decompose these equilibrium links into two main channels: First, the mega-firm channel, where a decrease in the number of firms results in the concentration of the offer distribution among a few large and highly productive firms. This leads workers in such firms to face a decrease in their job finding probability as better options outside their firm become scarce. Second, the retaliation channel, which precludes workers from re-matching with firms they are bargaining with. The retaliation channel interacts with the mega-firm channel in amplifying the wage response to a decrease in the number of firms.

I evaluate the model against the 2012-17 US labor market by simulating a decrease in the number of firms per worker in the model. I find that the model can account for about 2/3rd of the decline in job-to-job transitions and about 18 percent of the decrease in wages as a fraction of productivity between the 1980s and 2010s.

To evaluate the model's predictions, I examine the behavior of the model-relevant measure of labor market competition in the data. Using the data on firms and workers from the Business Dynamics Statistics (BDS) of the US Census Bureau, I document a persistent and long-run decline of about 18% in the firm-to-worker ratio for the aggregate US economy between 1979-2018 (Figure 1). I further document that the decline is pervasive within states, industrial sectors, and state-by-sector pairs, ruling out the hypothesis of it being a consequence of compositional changes that have taken place over the same period. I show that the long-run trends in firms per worker co-move with the employment concentration measures of Autor, Dorn, Katz, Patterson & Van Reenen (2020) for the super-sectors of the US.

Next, I explore the link between the evolution of firms per worker and the model-relevant outcome variables: Employer-to-Employer (EE) transitions, wages relative to productivity, and the wage growth associated with continuous job spells and EE transitions. To examine this link in the cross-section of US sub-markets, I combine data in the BDS with publicly available data on worker mobility from the Longitudinal Employer-Household Dynamics (LEHD), payroll share of gross value added from the Bureau of Labor Statistics (BLS), worker-firm demographics from the Quarterly Workforce Indicators (QWI) of the LEHD, as well as micro-data from the Survey of Income and Program Participation (SIPP).

In line with the predictions of the model, four findings are noteworthy. First, I document a positive correlation between the number of firms per worker and EE transitions rate across local labor markets defined as Metropolitan Statistical Area (MSA)-sector pairs, using a rich set of fixed effects and controlling for workforce composition by the worker and firm demographic groups. Second, I document a positive relationship between the number of firms per worker and the payroll share of value-added, which proxies wages as a share of productivity across disaggregated industries. Third, the number of firms per worker correlates negatively with wage growth associated with job switches and positively with the wage growth of job stayers, controlling for individual and job-specific characteristics. Fourth, in the spirit of recent work that examines the effect of market concentration measures on wages (Azar, Marinescu & Steinbaum 2020, Marinescu, Ouss & Pape 2020), I run instrumental variable regressions of average wages of labor market transitioners on the number of firms per worker, where the instrument captures the variation in the local firms to worker ratio that is driven by economy-wide changes in that sector. I document a positive relation between firms per worker and average wages. Overall, the empirical evidence on EE transitions rate, wage growth, and average wage levels is consistent with the model's predictions.

Related literature. My theoretical and empirical findings contribute to the large literature exploring the role of employer market power on labor market outcomes. Two studies are closely related to the model presented in this paper. First, Jarosch, Nimczik & Sorkin (2021) consider finite firms in a standard Diamond-Mortensen-Pissarides model where firms can remove their vacancies from the outside options of unemployed workers. The second, Schubert, Stansbury & Taska (2022), presents a framework with finite firms in which outside options of workers are a function of market concentration. Both studies predict that wages are inversely related to market concentration. The model presented in this paper differs from these studies in two important respects: First, in contrast to the work highlighted above, workers can search on-the-job, and firms compete for employed and unemployed workers. This is motivated by recent work by Faberman, Mueller, Şahin & Topa (2022) who show not only that on-the-job search is ubiquitous but also that employed workers receive more solicited and unsolicited employer contacts than unemployed workers. Second, as a result of introducing on-the-job search, the model presented here offers a novel market-power-based explanation for the falling EE transitions rate, apart from falling wages.[4]

Other theoretical models studying imperfect competition in the labor market and its implications on average wages and labor share have introduced firm market power through different channels. Berger, Herkenhoff & Mongey (2022) develop a general equilibrium model of labor market oligopsony where a finite number of differentiated firms in local labor markets face upward-sloping supply curves and compete strategically. Their model predicts that firms with larger market shares face smaller labor supply elasticity and pay wages that represent more considerable markdowns relative to the marginal revenue product of labor. Relatedly, Azkarate-Askasua & Zerecero (2020) develop a general equilibrium model where employers face an upward-sloping labor supply curve, and wages are collectively bargained between employers and worker unions. Both forces create wage distortions relative to the marginal revenue product, and their removal leads to gains in output, labor share, and welfare. Gouin-Bonenfant (2022) builds a search model where the key source of market power is productivity dispersion among firms. High-productivity firms are isolated from wage competition and can grow faster by poaching workers from other firms. The model predicts a fall in aggregate labor share in response to an increase in productivity dispersion driven by the reallocation of value-added towards

[4]Contemporaneous work by Berger, Herkenhoff, Kostol & Mongey (2022) studies the effect of employment-based Herfindahl Hirschman Indices (HHIs) on job flows, wages, and wage inequality in Norway. They find a negative correlation between HHIs and job flows and wages, in line with the results presented in this paper.

high-productivity firms.

The empirical strand of this literature documents the trends in employer market power in the aggregate and local labor markets and estimates its effects on average wages. Yeh, Macaluso & Hershbein (2022) measure employer market power through plant level wage markdowns and find evidence of its consistent rise from the early 2000s. Other studies compute concentration measures such as employment share of the largest firms in an industry, as well as Herfindahl Hirschman indices in employment (Autor, Dorn, Katz, Patterson & Van Reenen 2020, Benmelech, Bergman & Kim 2020, Rinz 2020), hires (Marinescu, Ouss & Pape 2020), and vacancies (Azar, Marinescu, Steinbaum & Taska 2020, Azar, Marinescu & Steinbaum 2020). These studies document a negative correlation between the relevant measure of market concentration and average wages. Finally, two recent and related studies also document the relation between firm market power and workers' outside options. First, Caldwell & Danieli (2022) measure the cross-sectional competition faced by a worker from other similar workers across jobs to arrive at the worker's relevant outside options. They find a positive correlation between outside options of German workers and their wages. Second, Schubert, Stansbury & Taska (2022) compute a measure of outside options by examining the availability of local jobs outside a worker's occupation. They document a positive and significant effect of an increase in the value of job options outside a worker's occupation on wages.

Overall, I contribute to the empirical strand of this literature by proposing a new measure of firm market power that validates the measure of competition in the proposed model. I demonstrate that the firms per worker across local labor markets relate closely to measures of employment concentration. I then document a positive link between firm competition and EE flows in the cross-section of MSA-sector pairs. The measure of firm competition proposed here also reaffirms the findings of the current literature, which has emphasized the effect of market power on wages, much like its theoretical counterpart.

The rest of the paper is organized as follows. Section 2 develops the model of the labor market and discusses its key features. Section 3 describes the calibration methodology and examines the model fit. It provides further details of the qualitative and quantitative implications of the model. Section 4 presents an empirical examination of key predictions of the model on wages and job transitions. Section 5 concludes.

2 Model

This section builds an equilibrium framework of the frictional labor market to establish the link between firm competition, worker mobility, and wages. The model features EE quits enabled through workers searching on-the-job and firms poaching workers from each other. Second, wages that respond to the value of the worker's current and prior match. Third, channels to decrease inter-firm competition, including finite firms that can retaliate against potential employees.

2.1 Agents

The continuous-time economy is populated by a unit continuum of homogeneous and infinitely lived workers. Each worker has linear preferences over the single good in the economy. Workers can be unemployed or employed. Unemployed workers derive flow value from leisure, and employed workers supply a unit of labor to firms, and are paid a wage ω.[5]

There is a finite number of firms in the economy that are heterogeneous in productivity. The total number of productivity levels is fixed to N, and firm productivity is denoted by $\theta_i \in \{\theta_1, ..., \theta_N\}$. Assume that productivity is uniformly distributed across firms such that firms can be ranked by their productivity: $\theta_1 < \cdots < \theta_N$. At each productivity level, there are $n(\theta_i) \equiv n_i$ number of homogeneous firms. Thus, the total number of firms in the economy is $\sum_{i=1}^{N} n_i$. Each period, firms offer jobs that are either filled or remain vacant. Filled jobs grant firms the flow value of the output produced, less wages paid, and vacant postings give firms no value.

The common discount rate of both agents is $\gamma \in (0, 1)$.

2.2 Matching

Firms and workers match through a random search process. Unemployed and employed workers meet firms with exogenous probabilities λ_0 and λ_1, respectively. All workers sample jobs from an exogenous job offer distribution F, with density f. Thus, the probability of an offer arising from a firm with a productivity level θ_i is $n_i \cdot f(\theta_i)$. I normalize $\sum_{i=1}^{N} n_i f(\theta_i) = 1$. On matching, firms and workers produce output equal to the firm's productivity. Matches are destroyed at an exogenous separation rate δ, in which case the worker flows into unemployment and the job becomes vacant.

2.3 Wage Bargaining

On matching, workers and firms bargain over wages, where the worker's bargaining share is denoted by $\alpha \in [0, 1]$. I assume that wages are pinned down following the sequential

[5]The exposition of the model is related to Jarosch (2021).

auction framework by Cahuc, Postel-Vinay & Robin (2006). This protocol ensures that the bargained wage implements a split of the match value, such that the worker receives a share equal to the average of their outside option and the joint match value, weighted by their bargaining share. The wage negotiation protocol can be described in more detail by way of an example.

Consider a worker who is employed at an incumbent firm of productivity $\theta_i \in \{\theta_1, ..., \theta_N\}$, and previously worked at another firm-$\theta_j \leq \theta_i$. I refer to the value that the worker received from the last firm she bargained with as her outside option. Wages, denoted by $\omega(\theta_i, \theta_j)$, are negotiated between firm-θ_i and the worker based on her outside option at firm-θ_j. Denote the worker's value as $W(\theta_i, \omega(\theta_i, \theta_j)) \equiv W(\theta_i, \theta_j)$, firm's value as $J(\theta_i, \theta_j)$, and the joint value of the match as $V(\theta_i) = W(\theta_i, \theta_j) + J(\theta_i, \theta_j)$.[6] Suppose the worker gets an offer on-the-job from a poaching firm of productivity θ_x. This triggers competition between the incumbent and poaching firms over the worker's labor services. The outcome of the game depends on which firm is more productive and can offer the worker a higher value. Three cases are possible.

First, consider the case when $\theta_x \geq \theta_i$. Then, in a bid to retain the worker, the incumbent firm revises the worker's wage upwards, offering her the entire match output as wage. As a result, wages are de-linked from the worker's previous employment at θ_j, and can be denoted as $\omega(\theta_i, \theta_i) = \theta_i$. The new wage grants the worker the entire match value, $W(\theta_i, \theta_i) = V(\theta_i)$. This comprises her new outside option when negotiating wages with the poaching firm-θ_x. The resulting wage offered by the poaching firm, $\omega(\theta_x, \theta_i)$, leaves the worker with a value equal to her new outside option, and $\alpha-$share of the increment in the joint match value that results from the worker quitting the less-productive incumbent firm, and joining the more-productive poaching firm:[7]

$$W(\theta_x, \theta_i) = W(\theta_i, \theta_i) + \alpha \cdot \big(V(\theta_x) - W(\theta_i, \theta_i)\big) \tag{1}$$

The new wage offered by the poaching firm promises the worker at least as much value as the one offered by the incumbent firm. The worker, therefore, accepts the offer of the poaching firm and makes a job-to-job transition from firm-θ_i to firm-θ_x.

Next, consider the case when $\theta_j < \theta_x < \theta_i$. Now, the poaching firm offers the worker the maximum wage equal to the potential match output θ_x, which comprises the worker's new outside option in place of the one at firm-θ_j. The revised outside option triggers rene-

[6]The joint value of a match V is not a function of a worker's prior employment, and only depends on the current employer's productivity. This will be clear from the value functions defined in the next section.

[7]This wage is an outcome of Nash bargaining between the worker and the poaching firm and the expression is formally derived in the Appendix A.1.

gotiation of the current wage between the worker and the incumbent firm. The resulting wage, $\omega(\theta_i, \theta_x)$, re-splits the match value, which leaves the worker with her revised outside option and $\alpha-$fraction of the incremental match value from forgoing the offer of the poaching firm:

$$W(\theta_i, \theta_x) = W(\theta_x, \theta_x) + \alpha \cdot \big(V(\theta_i) - W(\theta_x, \theta_x)\big) \tag{2}$$

The worker receives a value from firm-θ_i that is at least as high as the one offered by the poaching firm. She, therefore, accepts the revised wage offer and stays at her current employer. Note that in a finite firm setting, the worker can get a poaching-firm offer from any of the remaining $n_i - 1$ firms at θ_i. In that case, I assume the worker is equally likely to stay on the job or make a job-to-job transition from the incumbent to the poaching firm. Finally, if $\theta_x \leq \theta_j$, then the maximum wage offered by the poaching firm cannot exceed the worker's current outside offer from θ_j. It is, therefore, not in the interest of the worker to trigger a renegotiation game with the current employer. In this case, the worker stays with the same employer at an unchanged wage.

More generally, when a worker employed at some firm-θ_j, receives an offer from a more productive firm-θ_i, the wage negotiated between the worker and firm-θ_i competes with the worker's value from firm-θ_j. The latter includes the flow value from the match, equal to output θ_j, and the option value of job search from firm-θ_j. On-the-job search from firm-θ_j includes the possibility of receiving an offer from firm-θ_i. Thus, the worker's outside options contain, with non-zero probability, the possibility of a future match with firm-θ_i. In other words, while negotiating wages, firm-θ_i competes with the possibility of the worker sampling its own offer again in the future.

In a finite firm framework where each firm has a non-zero share in the offer distribution, I assume that while bargaining with the worker, firm-θ_i is allowed to remove its future offer from the worker's outside option at firm-θ_j. This has the effect of discounting the worker's outside option and the resulting wage offered. Thus, in the spirit of Jarosch, Nimczik & Sorkin (2021), I assume that firms do not allow their matched applicants to reapply from their outside option.[8] In other words, should the wage negotiation between the worker and firm-θ_i break down, leading the worker to avail her outside option at firm-θ_j, then she does not receive the option value of matching with firm-θ_i again through on-the-job search at firm-θ_j. It is important to note that the penalty imposed on the worker does not occur in equilibrium, as the negotiation between the worker and firm never breaks

[8]Note that in the context of homogeneous workers, it is optimal for the firm to not make a future offer to a particular matched applicant if that applicant is not the only one who matches with the firm. I assume that the probability of the firm matching in the future with that particular applicant and that applicant being the only match for the firm's vacancy is approximately zero. Jarosch et al. (2021) compute this probability from matched employer-employee data from Austria and find it to be very small.

down. Despite that, this mechanism affects the equilibrium outcomes of the model. For the sake of tractability, I also assume that the penalty imposed on the worker only lasts for that employment spell, i.e., in the context of the example above, the worker is prevented from getting an offer from firm-θ_i only as long as she is employed at firm-θ_j.

Thus, while negotiating wages with firm θ_i, the worker's outside option is now denoted as $\widetilde{W}(\theta_j, \theta_j, \theta_i)$, i.e., the value offered by firm-θ_j excludes the option value of matching with firm-θ_i through on-the-job search. I re-specify equations (1) & (2) and re-write the wage setting equation:

$$W(\theta_i, \theta_j) = \widetilde{W}(\theta_j, \theta_j, \theta_i) + \alpha \cdot \big(V(\theta_i) - \widetilde{W}(\theta_j, \theta_j, \theta_i)\big) \tag{3}$$

It is useful to note that the discussion above can be extended to the case of an unemployed worker receiving a flow value from leisure, and the option value of search from unemployment. To be consistent with their employed counterparts, I assume that firms can exclude their future offers even for workers hired from unemployment. To see this, suppose an unemployed worker matches with firm-θ_i. Denote the outside option of such a worker who does not receive the option value from matching again with firm-θ_i as $\widetilde{U}(\theta_i)$. Then the reservation wage negotiated by the unemployed worker and firm-θ_i solves:

$$W(\theta_i, \theta_u) = \widetilde{U}(\theta_i) + \alpha \cdot \big(V(\theta_i) - \widetilde{U}(\theta_i)\big) \tag{4}$$

Here θ_u is the reservation productivity level that leaves the worker indifferent between staying unemployed or employed at firm-θ_u. Thus, the value received by a worker hired from unemployment by firm-θ_i is a linear combination of her outside option from unemployment, excluding the option value of matching with firm-θ_i, and the net increment in joint value as a result of the match.

In the next section, I describe the value functions introduced thus far.

2.4 Value Functions

This section formalizes the recursive equations of the model. For an employed worker at firm-θ_i with an outside option at firm-θ_j, the value function is denoted by:

$$
\begin{aligned}
(\gamma+\delta)W(\theta_i,\theta_j) &= \omega(\theta_i,\theta_j)+\delta U \\
&+ \lambda_1 \Bigg\{ \sum_{x=i+1}^{N} \Big(W(\theta_x,\theta_i) - W(\theta_i,\theta_j) \Big) n_x f(\theta_x) \\
&+ \sum_{x=j+1}^{i-1} \Big(W(\theta_i,\theta_x) - W(\theta_i,\theta_j) \Big) n_x f(\theta_x) \\
&+ \Big(W(\theta_i,\theta_i) - W(\theta_i,\theta_j) \Big) (n_i - 1) f(\theta_i) \Bigg\}
\end{aligned} \tag{5}
$$

The employed worker receives a flow payoff equal to the current wage, $\omega(\theta_i, \theta_j)$. Next period the worker may be exogenously separated from the firm with probability δ and flow into unemployment, receiving a value U. If the worker is not separated and stays on the job, she may contact and sample an offer from a firm with productivity θ_x, with probability $\lambda_1 n_x f(\theta_x)$. If $\theta_x > \theta_i$, then the worker makes a job-to-job transition to firm-θ_x. If $\theta_i > \theta_x > \theta_j$, the worker gets a within-job wage revision. If the worker samples from any one of the remaining $(n_i - 1)$ firms at productivity θ_i, she is indifferent between staying at θ_i or joining the poaching firm as both firms offer the same value. In such instances of a tie between the incumbent and poaching firms, the worker is equally likely to be a job stayer or job switcher. With the remaining probability, she does not match with any firm, matches with a firm that is less productive than θ_j, or matches with her own employer again, and her value remains unchanged.

Now suppose a worker who is employed at θ_i, gets an on-the-job offer from some firm-$\theta_h > \theta_i$. Then the worker's outside option, denoted by $\widetilde{W}(\theta_i, \theta_i, \theta_h) \equiv \widetilde{V}(\theta_i, \theta_h)$, includes the entire match value from firm θ_i without the option value of matching at firm-θ_h through on-the-job search. This can be expressed as:

$$
\begin{aligned}
(\gamma+\delta)\widetilde{W}(\theta_i,\theta_i,\theta_h) &= y(\theta_i)+\delta U \\
&+ \lambda_1 \Bigg\{ \sum_{x=i+1}^{N} \Big(W(\theta_x,\theta_i) - \widetilde{W}(\theta_i,\theta_i,\theta_h) \Big) n_x f(\theta_x) \\
&- \Big(W(\theta_h,\theta_i) - \widetilde{W}(\theta_i,\theta_i,\theta_h) \Big) f(\theta_h) \\
&+ \Big(W(\theta_i,\theta_i) - \widetilde{W}(\theta_i,\theta_i,\theta_h) \Big) (n_i - 1) f(\theta_i) \Bigg\}
\end{aligned} \tag{6}
$$

To retain the worker, firm-θ_i bids up the wage to its maximum level, such that the worker gets the entire match output, $y(\theta_i)$. The option value of search excludes the possibility of sampling a job from a firm with productivity θ_h. This is shown in the third line where the worker's value from a firm at θ_h is removed from the potential offers that she can receive on the job. Note that the preclusion of firm-θ_h's offer only lasts through the worker's employment spell at firm-θ_i. If the worker joins any other firm or gets matched with a firm at the same productivity, her value function is no longer $\widetilde{W}$ but W. This simplifying assumption reduces the dimensionality of the value function by preventing the need to keep track of the full history of precluded firms from the worker's offer distribution.

The value function of an unemployed worker satisfies:

$$\gamma U = z + \lambda_0 \sum_{x=u+1}^{N} \Big(W(\theta_x, \theta_u) - U \Big) n_x f(\theta_x) \tag{7}$$

The unemployed worker receives a flow payoff from leisure, z, and with probability λ_0, contacts a firm. If that firm is more productive than an unknown threshold productivity level, θ_u, the worker accepts the job and flows into employment.[9] With the remaining probability, including not receiving a job offer or receiving one from a firm at or below θ_u, the worker remains in the state of unemployment.

Suppose the unemployed worker matches with some firm-$\theta_h > \theta_u$. Then, to be consistent with her employed counterpart, the worker's outside option precludes the vacancy of that firm. The outside option can be expressed as:

$$\gamma \widetilde{U}(\theta_h) = z + \lambda_0 \Bigg[\sum_{x=u+1}^{N} \big(W(\theta_x, \theta_u) - U(\theta_h) \big) n_x f(\theta_x) - \big(W(\theta_h, \theta_u) - U(\theta_h) \big) f(\theta_h) \Bigg] \tag{8}$$

The outside option of the worker hired from unemployment by firm-θ_h is similar to the value from unemployment defined in equation (7), except it excludes a vacancy from firm-θ_h in the option value of job search from unemployment.[10]

The value of a filled job to a firm at θ_i, with a worker whose outside option is at a firm at θ_j satisfies:

$$\gamma J(\theta_i, \theta_j) = y(\theta_i) - \omega(\theta_i, \theta_j) + \lambda_1 \sum_{x=j+1}^{i-1} \Big(J(\theta_i, \theta_x) - J(\theta_i, \theta_j) \Big) n_x f(\theta_x) \tag{9}$$

The flow payoff to the firm from a match is equal to the output, $y(\theta_i)$, less the wages

[9] θ_u is the reservation productivity level, i.e., the level at which the worker is indifferent between being unemployed or employed at a firm with that productivity and receiving the entire match value. Thus, $U = W(\theta_u, \theta_u)$. The unemployed worker accepts all offers from firms that are more productive than θ_u. Note that θ_u is an unknown object of the model, and I assume a single firm at the reservation productivity level, i.e., $n_u = 1$. Being the least productive firm, it cannot exclude its offer from the outside option of a worker.

[10] One outcome of the model is that $\widetilde{U}(\theta_u) = U$, i.e., exclusion of an offer from the firm at θ_u is immaterial for the unemployed worker.

paid to the worker. If the firm and worker separate in the next period, either exogenously or through worker-quits, the job becomes vacant, and the firm's continuation value is zero. If the firm and worker do not separate, and the worker samples an offer from a firm that is less productive than θ_i, but more productive than θ_j, then the match value is re-split, and the firm receives a revised share. If the worker contacts another firm at the same productivity θ_i, then the worker gets the entire match value and the firm gets zero. Finally, if the worker does not contact a firm that is more productive than firm-θ_j, then the firm's continuation value remains the same.[11]

As outlined in Appendix A.1, Nash bargaining implies that the bargained wage, $\omega(\theta_i, \theta_j)$, solves equation (3). When employed at firm-θ_i with an outside option at firm-θ_j, the worker receives a value that is a weighted average of the match value at θ_i, $W(\theta_i, \theta_i) = V(\theta_i)$, and the outside option at θ_j, $\widetilde{W}(\theta_j, \theta_j, \theta_i)$. The model solution is described in the next section.

2.5 Solving the Model

The value functions in equations (5)-(9), along with solutions to Nash bargaining in (3) can be expressed in terms of a functional equation $-$ the joint value function $-$ defined as the total match value between a worker and firm, $\widetilde{V}(\theta_i, \theta_h), \forall h \geq i$. When $h = i$, the joint value takes the form, $\widetilde{V}(\theta_i, \theta_i) = V(\theta_i)$. The value from unemployment can be expressed in terms of joint value at firm-θ_u, $U = V(\theta_u)$. Thus, the model can be expressed in terms of the following two equations:

$$\begin{aligned}(\gamma + \delta)\widetilde{V}(\theta_i, \theta_h) &= y(\theta_i) + \delta V(\theta_u) \\ &\quad + \lambda_1 \Bigg\{ \sum_{x=i+1}^{N} \Big[(1-\alpha)\widetilde{V}(\theta_i, \theta_x) + \alpha V(\theta_x) - \widetilde{V}(\theta_i, \theta_h)\Big] n_x f(\theta_x) \\ &\quad - \alpha \Big[V(\theta_h) - \widetilde{V}(\theta_i, \theta_h)\Big] f(\theta_h) + \Big[V(\theta_i) - \widetilde{V}(\theta_i, \theta_h)\Big](n_i - 1) f(\theta_i) \Bigg\}, \forall h \geq i\end{aligned} \tag{10}$$

$$y(\theta_u) = z + (\lambda_0 - \lambda_1) \Bigg\{ \sum_{x=u+1}^{N} \Big[(1-\alpha)\widetilde{V}(\theta_u, \theta_x) + \alpha V(\theta_x) - V(\theta_u)\Big] n_x f(\theta_x) \Bigg\} \tag{11}$$

[11]Note that throughout the model, the value of keeping a job opening vacant is assumed to be zero. In a version of this model with an endogenous vacancy creation decision, this condition can be achieved by assuming that the cost of posting a vacancy to a firm is firm productivity-specific. With this assumption, the entire model can be solved without specifying the firm's value from a vacant posting.

The left-hand side of the equation (10) is the present discounted joint value of a match between a worker and firm-θ_i, which does not include an on-the-job offer for the worker from the more productive firm-θ_h. The first term on the right-hand side captures the flow payoff from the match to the worker and firm, $y(\theta_i)$. The second term captures the event of the match coming to an end, and the worker receiving the net value from unemployment. The third and fourth terms capture the event of the worker receiving an outside offer from any firm, except one with productivity θ_h, that is more productive than θ_i, and that poaches the worker away from firm-θ_i. The worker receives a value equal to the weighted average of the joint values from the poaching and incumbent firms, net of the value lost at the incumbent firm. Finally, the last term captures the possibility of the worker receiving an offer from any one of the remaining firms at the same productivity level as the incumbent firm, and effectively getting released from the penalty imposed by firm-θ_h. Finally, the match continues on current terms if the worker does not receive a job offer, or receives one from the incumbent firm at θ_i.

Equation (11) provides a numerical expression for the unknown reservation productivity level, θ_u. The output from the reservation productivity level is a function of the flow value from leisure, and the continuation value from employment at any firm more productive than θ_u. The latter is weighted by the difference between the job finding rate of the unemployed and employed.

The model can be fully summarized by equations (10) and (11) and two unknowns ($\widetilde{V}$ and θ_u), making the system tractable. The algorithm for solving the model numerically is detailed in Appendix A.2. Finally, the equilibrium wage function is derived in Appendix A.3.

3 Quantitative Analysis

I solve the model described in the previous section and simulate an economy based on its equilibrium outcomes. In this section, I first describe the calibration strategy to determine the model's parameters. This is followed by comparing the simulated moments at the optimally chosen parameter values with their empirical counterparts to assess the model's fit. Finally, I show a counterfactual economy with the varying market power of firms and evaluate the model's qualitative and quantitative predictions.

3.1 Calibration

The model is calibrated at a monthly frequency. As the model's economy is in steady-state, its moments are targeted to match long-run averages of empirical moments for the US economy. Specifically, the model is calibrated to the 1985-90 economy and evaluated against the 2012-17 economy.[12] In what follows, I describe the empirical moments targeted in the calibration exercise and discuss how they are informative about the model's parameters.

First, the contact probabilities of the employed (λ_1) and unemployed (λ_0) are informative about the average monthly transition probability from employment-to-employment (EE), and unemployment-to-employment (UE), respectively, and are chosen to target them. The exogenous separation rate, δ, informs about the employment-to-unemployment (EU) flow probability and the unemployment rate and is chosen to match the former. Following the methodology of Shimer (2012), I compute the long-run averages of the UE and EU transitions probabilities utilizing stocks of unemployment duration from the monthly Current Population Survey (CPS) from 1985m3-1990m3.[13] I arrive monthly UE and EU transitions probabilities averaging 44.9 percent and 3.78 percent, respectively. The monthly EE transition probability is computed over the same period following Diamond & Şahin (2016). They build on the methodology developed in Blanchard, Diamond, Hall & Murphy (1990) that uses EE transition measures of the Annual Social and Economic (ASEC) Supplement of the CPS. The annual estimates are linearly interpolated to arrive at quarterly measures of EE transitions. I express the quarterly transition probability as a monthly one and take long-run quarterly averages of the latter. The EE transition probability over this period averages 2.83 percent.

In the model, total firms are a product of the number of productivity levels on the job ladder (N) and the vector of the number of firms at each productivity level $(n(\theta))$. I interpret N as the average number of tiers in a worker's lifetime job ladder. This is set to five and lies within the range observed in the literature on career ladders (Forret & Dougherty (2004), Caliendo, Monte & Rossi-Hansberg (2015), four; Bayer & Kuhn (2018), five).[14]

[12]These periods are chosen because they observed similar unemployment rates (around 6.2 percent) and considerably different levels of employer competition (discussed in more detail in the next section). All the results of the calibration exercise are qualitatively similar if the model is calibrated to target long-run averages of 1990-2017. The results also remain similar if the model targets 2012-17 and is evaluated against 1985-90.

[13]Monthly UE hires probability is computed by subtracting from the unemployed of the previous month, the number of workers who have been unemployed for more than a month, to arrive at the number of workers who exited unemployment from the last month to the current month. This is expressed as a fraction of the number of unemployed workers in the previous month. The EU separations probability is computed by plugging the hires probability into the steady-state unemployment rate.

[14]I set the number of employer-firm productivity levels to be five. This does not include θ_u, which is

Next, to determine the number of firms in the model, I use the employment-weighted firms per worker distribution across metropolitan area-sector pairs in 1985-90 in the BDS. First, I assume that each quintile of the empirical firms per worker distribution is an individual market in the model. Each market is treated as an isolated island, differing only in the number of firms from one another. To arrive at the number of firms from the empirical firms per worker distribution, I assume each quintile faces approximately 5000 workers, which was the mean employment in a MSA $\times$ sector in 1985-90. This assumption is made to get as close as possible to the notion of the number of firms in local labor markets. It also utilizes the dispersion in the distribution of firms per worker across markets. Next, the model is solved and simulated individually for each market. Finally, the aggregate moments in the model are computed by taking a weighted average of market-level moments. The weights correspond to the employment share of each quintile of the empirical firms per worker distribution. The number of firms in each market is 109.8, 267.2, 418.1, 625.8, and 1151.3. The employment-weighted average number of firms in the model is 265.7. The main advantage of setting the number of firms to match the distribution of firms per worker rather than its mean or median is to capture the non-linear response of model outcomes to changing firms per worker that is prevalent in markets with a smaller set of firms. Finally, I allow the market-specific number of firms to take on decimal values by expressing that market as a combination of several markets with an integer-valued number of firms. [15]

I set the five-dimensional vector $n(\theta)$ to match the distribution of firms over the job ladder. I approximate the job ladder by the firm size distribution, conditional on firm age and sector. The firm size is measured by the size of the workforce. Even though most search models featuring a job ladder postulate a positive relationship between firm size and productivity, Haltiwanger et al. (2018) observe evidence of a firm size ladder only after controlling for firm age. I, therefore, compute the firm size distribution averaging over

always assumed to be a productivity level with a single non-employer firm.

[15]Suppose the total number of firms in a market is distributed over a 2-D productivity grid according to the following: $\{n(\theta_1), n(\theta_2)\}$. Then each grid point can take on a decimal-valued number of firms by expressing the market as a weighted average of four markets with integer-valued number of firms:

$$\begin{pmatrix} n(\theta_1) \\ n(\theta_2) \end{pmatrix} = x_2 x_1 \begin{pmatrix} n(\theta_1)^- \\ n(\theta_2)^- \end{pmatrix} + x_2(1-x_1) \begin{pmatrix} n(\theta_1)^+ \\ n(\theta_2)^- \end{pmatrix} + (1-x_2)x_1 \begin{pmatrix} n(\theta_1)^- \\ n(\theta_2)^+ \end{pmatrix} + (1-x_2)(1-x_1) \begin{pmatrix} n(\theta_1)^+ \\ n(\theta_2)^+ \end{pmatrix}$$

where the superscript $-$ denotes the largest integer value less than or equal to the decimal value, and $+$ denotes the smallest integer value greater than or equal to the decimal value. The sum of all weights is 1, and each weight is uniquely determined by $x_i = n(\theta_i)^+ - n(\theta_i)$. In general, a productivity grid with N points requires combinations over 2^N markets to allow the number of firms at each grid point to take on decimal values. Importantly, treating the number of firms as integers or not only matters at higher productivity levels that face a small number of firms.

firm age groups and sectors. To find evidence of firms per worker over the firm size ladder, I use firm and employment counts in firm size, age, and sector cells from the BDS. The data on firm age are prone to being left-censored, and many of the firm age x size cells have missing values due to Census disclosure norms. To avoid the problem of left-censoring, I exclude all firm age data prior to 1988. To tackle the problem of missing observations, I aggregate the data into five firm size bins: 1-9, 10-19, 20-99, 100-499, and 500+ employees and three firm age bins: 1-5, 6-10, and 11+ years.[16] I fill in the missing firm age x firm size x sector cells by imputing their differences from the recently available data on coarse firm age and firm size bins provided by the BDS. Finally, I take employment-weighted averages of the firm size classes over all the firm age-sector cells to arrive at the firm size ladder for 1987-89. The main advantage of using a firm size ladder to proxy for the job ladder is the availability of data dating back to the 1980s. I arrive at the following distribution of the share of firms over the firm size bins: $\{0.612, 0.143, 0.166, 0.049, 0.027\}$. This is interpreted as, 61 percent of the sample of employers being in the lowest productivity tier of the job ladder, while three percent lie on the right tail.

Next, I set the job offer distribution to be beta with shape parameters ν and μ. These shape parameters, along with the bargaining power parameter of workers, α, jointly inform measures of wage dispersion and wage growth. These include the Mean-min (Mm) ratio, the standard deviation of offered wages, and wage growth associated with continuous job spells. In the model, decreases in α are associated with the declining bargaining power of all workers, including the unemployed. This affects the reservation wage of the unemployed and consequently the Mm ratio. The direction of the effect is based on whether it is easier to contact a job from unemployment or employment. At the same time, as α declines, the standard deviation of wages offered to UE hires get compressed towards their reservation wage, while that of EE hires is weighted more heavily by their outside option. Further, the two shape parameters of the job offer distribution determine the part of the job ladder where most offers originate. A higher mass at the lower tier of the distribution translates to a lower incidence of wage growth across jobs and a higher one within job spells. I target the standard deviation of offered wages to the one estimated by Hall & Mueller (2018). Using panel data on job seekers drawing unemployment benefits in New Jersey in 2009 (Krueger-Mueller Survey), they estimate the standard deviation, after controlling for the job seeker's productivity, to be 0.24. Further, I target the Mm ratio between 1.5 and 2, as documented in Hornstein, Krusell & Violante (2011). I compute wage growth over continuous 12-month job spells using the SIPP 1996-2000 panel.

[16] I exclude start-ups or age-0 firms. This makes no quantitative difference to the employment-weighted firm size distribution, except for making the values less unstable over time.

Table 1: Parameter Values

	Parameter	Value	Target/Source
		Externally Calibrated	
N	Productivity Levels	5	Bayer & Kuhn (2018)
$\sum_{i=1}^{N} n_i$	Mean Firms Across Markets	266	Emp-weighted FPW dist., MSA×Sector (BDS)
$\{n_i/\sum_{i=1}^{N} n_i\}_i$	Firm share|Job ladder	{0.61, 0.15, 0.17, 0.05, 0.03}	Firm share|Firm Size dist. (BDS, 1987-89)
γ	Discount Rate	0.004	4% annual interest rate
		Internally Calibrated	
λ_0	Contact Rate of Unemp	0.47	E [UE]
λ_1	Contact Rate of Emp	0.09	E [EE]
δ	Separations Rate	0.04	E [EU]
ν, μ	Job Offer Distn ∼ Beta	1.02, 0.68	SD (Log Wage Offers); w∆|Job Spell
α	Worker's Bargaining Share	0.46	Mean-min Ratio
z	Flow value of leisure	0.79	$z/$Average Labor Productivity

Notes: This table displays the calibrated parameter values of the model when the model is simulated at a monthly frequency. E[EU] and E[UE] stand for, respectively, the average worker flows into and out of unemployment, and E[EE] stands for average employment-to-employment flows. All flows are computed at a monthly frequency and averaged over a five-year horizon from 1985-90. SD(Wages) refers to the standard deviation of log offered wages. Mm ratio refers to the Mean to min ratio of the wage distribution. w∆|Job Spell denotes the average wage growth associated with 12-month continuous job spells. BDS stands for Business Dynamics Statistics. The total number of firms is the employment-weighted average of each quintile of the empirical firms per 5000 workers distributed across MSA-sector pairs between 1985-90.

Finally, the discount rate, γ, is set to match an annual interest rate of four percent. Output across all matches, $y(\theta_i)$, is expressed as θ_i additively scaled up by a constant output shifter, ζ_i. This is done so that the least productive firm produces non-zero output. I set the output shifter to 1. In the calibrated model, this implies the ratio of the flow value from leisure, net of the output shifter and as a fraction of the Average Labor Productivity (ALP) is in line with target range set in the literature (Shimer (2005), 0.4; Mas & Pallais (2019), 0.6; Hall & Milgrom (2008), 0.71 and Hagedorn & Manovskii (2008), 0.995).

The model's parameters are calibrated using the Simulated Method of Moments. This procedure aims at choosing those parameter values that minimize the distance between the model-simulated and corresponding data-generated moments. The model is identified using seven moments (averages of UE, EU, and EE transitions, the standard deviation of offered wages, the Mm ratio, and wage growth associated with continuous job spells) to inform seven parameters $(\lambda_0, \lambda_1, \delta, \nu, \mu, \alpha, z)$.

Table (1) shows the model's calibrated parameters that minimize the distance between the targeted and model-generated moments as well as its fixed parameters. Table (2) reports the simulated moments of the model at the calibrated parameters and their targeted counterparts. The model moments come close to delivering their targeted values.

Table 2: Model-generated Moments and their Targeted Values

Moment	Model	Data	Data Source
E [UE], %	46.7	44.9	CPS, 1985-90
E [EE], %	2.85	2.83	CPS, 1985-90
E [EU], %	3.89	3.79	CPS, 1985-90
SD (Log Wage Offers)	0.19	0.24	Hall & Mueller (2018)
E [Wage Growth, 12m Job Spell], %	0.52	0.90	SIPP, 1996-00
Mm Ratio	1.39	1.5-2	Hornstein, Krusell & Violante (2011)
z/ALP	0.42	0.40	Shimer (2005)

Notes: This table displays the model-simulated moments and their targeted counterparts, where the latter are used to arrive at the optimal parameter values. E[EU] and E[UE] stand for, respectively, the average worker flows into and out of unemployment, and E[EE] stands for average employment-to-employment flows. All flows are computed at a monthly frequency and averaged over a five-year horizon from 1985-90. SD(Wages) refers to the standard deviation of log offered wages. Mm ratio refers to the Mean to min ratio of the wage distribution. wΔ|Job Spell denotes the average wage growth associated with 12-month continuous job spells. ALP stands for Average Labor Productivity.

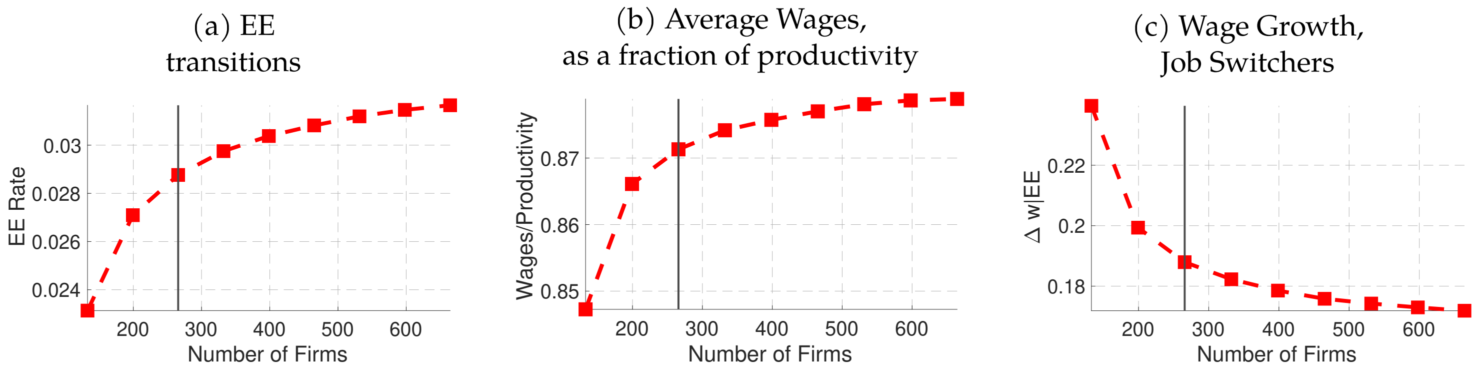
3.2 Equilibrium Effects of Declining Number of Firms

This section analyzes the model's implications when the number of firms varies from its baseline level. In particular, I hold the productivity of each firm at a fixed level and all parameters of the model at their calibrated values and only vary the number of firms, n_i, within each productivity level. I first explain the qualitative predictions of the model and evaluate the model's main mechanism. I then show the quantitative predictions of changing the number of firms.

3.2.1 Qualitative Implications

Figure (2) plots labor flow and wage moments generated by the model when the number of firms at each productivity level is varied by the same proportion, holding all other parameters of the model, including the distribution of firms over the job ladder, constant. The vertical line represents the calibrated model. Panel (2a) shows that EE transitions are increasing in the number of firms. As the number of firms on the job ladder uniformly declines, employees are less likely to receive offers from poaching firms. This reduces worker propensity to quit and make EE transitions. In the extreme case, suppose the most productive tier of the job ladder comprises only one firm, then all employees of that firm lose the option of making a job switch. As the most productive firms are also the largest in the model, a higher share of employees is prevented from making EE transitions if the incumbent firm faces no competition. On the other hand, as the competition intensifies,

Figure 2: Response of Model Outcomes to Changing Number of Firms



Notes: This figure displays the model-simulated moments in response to different values of the number of firms, holding all other parameters fixed at their calibrated values in Table (1). The x-axis of each panel denotes the total number of firms in the model. The vertical line represents the calibrated model.

the probability of getting an offer from a firm at the same or a higher productivity level increases resulting in a higher number of quits.

Panel (2b) shows that wages/productivity are also increasing in the number of firms. This happens for two reasons: First, average real wages are determined by workers' outside options. As the number of firms decreases, so does the option value of search from the incumbent firm. This reduces the value of the match and, therefore, directly affects wages relative to productivity. Second, the strong non-linearity in the plot is due to firms imposing a penalty on re-applicants. In an environment with many firms in the market, each firm has a lower share in the offer distribution, and the market converges towards one with atomistic firms. This diminishes firms' ability to penalize workers by removing their offers from workers' outside options. Thus, competition intensifies with an increasing number of firms trying to poach and retain workers, increasing workers' value and bidding up wages. However, the opposite is true as competition dampens. Suppose there is a single firm at a given productivity level, and that firm's vacancy is precluded from the worker's job search. In that case, the worker faces a reduction in their job-finding probability that is tantamount to losing a tier of the job ladder. This leads to a considerable decrease in wages.

The growth rates of wages associated with job switches is shown in panel (2c). As competition in the economy increases, workers are more likely to get higher wage offers from poaching firms. In trying to match such offers, incumbent firms offer an even higher wage to retain the workers, leading to a higher average wage level for stayers. As a result, workers face a higher likelihood of maxing out on their wages before making a job switch, thereby decreasing the wage growth associated with EE transitions. At the other end of the spectrum, when workers face fewer firms, they are much more likely to stay longer on the same job, and at a suppressed wage, such that there is more room for wages to increase when workers switch jobs.

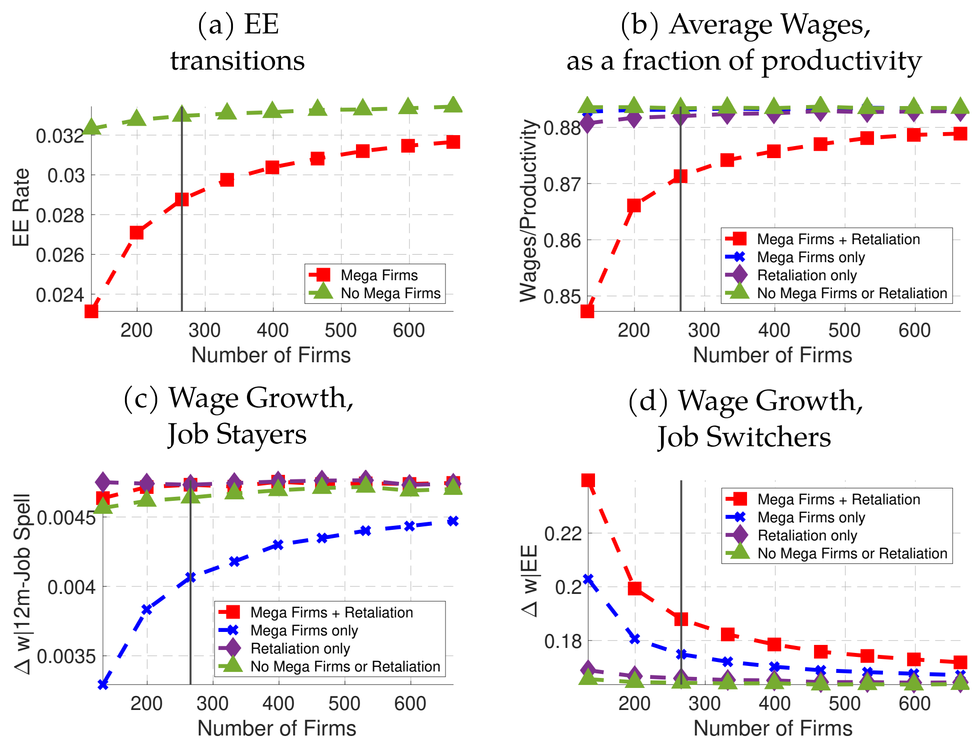
In terms of equilibrium response of the model's functions, as competition in the economy intensifies, the value to the employed and unemployed worker increases while that to the firm reduces. This happens because as firms become increasingly atomistic, their ability to discount workers' outside options diminishes. As their outside options grow, workers receive a more significant split of the match value, resulting in high worker- and lower firm value. The joint value of the match increases in the number of firms as employed workers' value increases more than the reduction in firm value. Further, as competition intensifies, firms are also less able to penalize unemployed workers by removing their vacancies from their outside options. This makes the unemployed workers pickier in setting the threshold productivity level above which they begin accepting offers. Thus, the reservation productivity level, θ_u, increases with rising competition. I omit the plots of the equilibrium functions of the model.

3.2.2 Main Mechanisms of the Model

The main channels through which the changing number of firms drives the model outcomes can be summarized as the following: (1) *Mega Firm Channel*: For a given distribution of firms and offers over the job ladder, a decrease in the number of firms makes every firm larger. As employment becomes concentrated in large firms, workers in these firms face a reduced probability of job finding. This reduces the worker's value from searching on the job and, therefore, their share of the joint value. (2) *Retaliation Channel*: Workers can no longer match with their incumbent firm from their outside option or prior match. As part of the worker's value from their prior match accrues from searching on the job and matching with the incumbent firm, the worker loses part of the option value of searching from their prior match. This discounts the value of the prior match. Thus, when bargaining with the incumbent firm, the worker has a lower threat point, which reduces the worker's share of the joint value. Both model mechanisms are enabled through the worker searching on the job, either from the incumbent firm or their prior match.

To further understand the main channels of the model and their interactions, it is useful to consider four versions of the model: (1) *Allowing Mega Firm and Retaliation Channels*: This is the benchmark version of the model shown in red in Figures 2 and 3. (2) *Allowing Mega Firms Channel Only*: This version of the model switches off the retaliation channel, i.e., incumbent firms no longer penalize workers' outside options. (3) *Allowing Retaliation*

Figure 3: Decomposing the Response of Model Outcomes to Changing Number of Firms



Notes: This figure displays the model-simulated moments in response to different values of the number of firms, holding all other parameters fixed at their calibrated values in Table (1). The figure distinguishes between four versions of the model: (1) The benchmark model with the mega-firm and retaliation channels, (2) A version of the model with mega firms only, without retaliation. (3) A version of the model with uniformly distributed firms over the productivity grid that are allowed to retaliate. (4) A model without mega firms and retaliation. The x-axis of each panel denotes the total number of firms in the model. The vertical line represents the calibrated model.

Channel Only: This model version allows firms to retaliate. It switches off the mega-firm channel, which is enabled through the skewed distribution of firms over the job ladder. Instead of assuming the firm distribution given in Table 1, i.e., $\{0.61, 0.15, 0.17, 0.05, 0.03\}$, I assume all firms are distributed uniformly over the productivity grid, i.e., $\{0.2, 0.2, 0.2, 0.2, 0.2\}$. (4) *Switching off Mega Firm and Retaliation Channels*: This model version switches off retaliation and mega-firms and strips down to the finite firm version of the baseline Cahuc, Postel-Vinay & Robin (2006) model. All firms are distributed uniformly over the productivity grid.

Figure (3) plots the four distinct versions of the model, holding all parameters at their calibrated values and only changing the number of firms. The red line in each panel presents the benchmark model with mega firms and retaliation channels, which is also depicted in Figure (2).

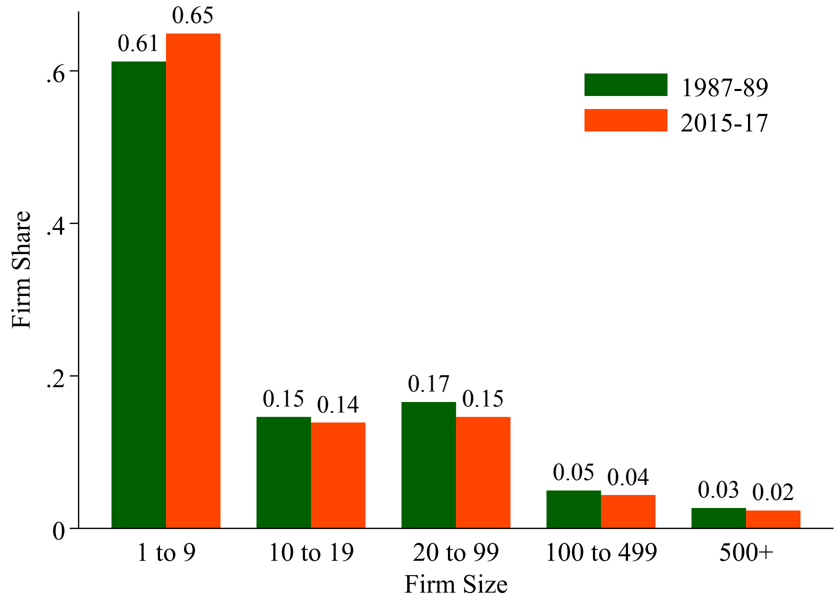
Panel (3a) shows that the EE transitions rate is increasing in the number of firms across the two versions of the model, with and without mega-firms. Compared to a model with uniformly distributed firms (green line), in a model with mega-firms (red line), firms at the top of the job ladder are fewer and, therefore, larger. This amplifies the decline in EE transitions as the number of firms further decreases. Note that the retaliation channel has no effect on any realized worker transition; therefore, the EE transitions rate in models with and without retaliation coincide.

Panel (3b) shows that across all versions of the model, wages/productivity are non-decreasing in the number of firms. Out of all model specifications, the retaliation channel is crucial for generating a wage response to a changing number of firms, and it is the interaction of the retaliation and mega-firm channels (red line) that amplifies the wage response relative to a model with the retaliation channel alone (purple line). The absence of the retaliation channel (blue and green lines) leads to a nearly flat wage response.

Panels (3c) and (3d) show that, for all versions of the model, the wage growth associated with continuous job spells is positively related to the number of firms and that associated with EE transitions is negatively related to the number of firms. To understand the model behavior across different channels for a given number of firms, I first hold the mega-firm channel constant and compare the model with retaliation (red line) to the one without retaliation (blue line) in Panels (3c) and (3d). As wage levels are suppressed relative to productivity in the presence of retaliation (Panel 3b), there is more room for wages to grow, both across and within firms. This means both job stayers and switchers realize a larger wage growth in models with retaliation compared to models without retaliation. This is seen by the red line (with retaliation) being above the blue line (without retaliation), and the purple line (with retaliation) being above the green line (without retaliation) in Panels (3c) and (3d).

Second, now hold the retaliation channel constant and compare the models with mega firms (red line) and without mega firms (purple line). For a given number of firms, the model with mega-firms has less competition among firms. Thus, in a model with mega-firms, relative to one without, we see higher wage growth of job switchers and lower wage growth of job stayers. Notice that this follows intuitively from Figure(2c), where in an environment of low competition due to fewer firms, wage growth of job switchers is high. This explains why for the job switchers, the red line (with mega-firms) is above the purple line (without mega-firms), and the blue line (with mega-firms) is above the green line (without mega-firms). This also explains why for the job stayers, the red line (with mega-firms) is below the purple line (without mega-firms), and the blue line (with mega-firms) is below the green line (without mega-firms).

Figure 4: Firm Share over Firm Size Bins, 2015-17 and 1987-89



Notes: This figure shows the firm share over the firm-size ladder in 1987-89 and 2015-17. Business Dynamics Statistics.

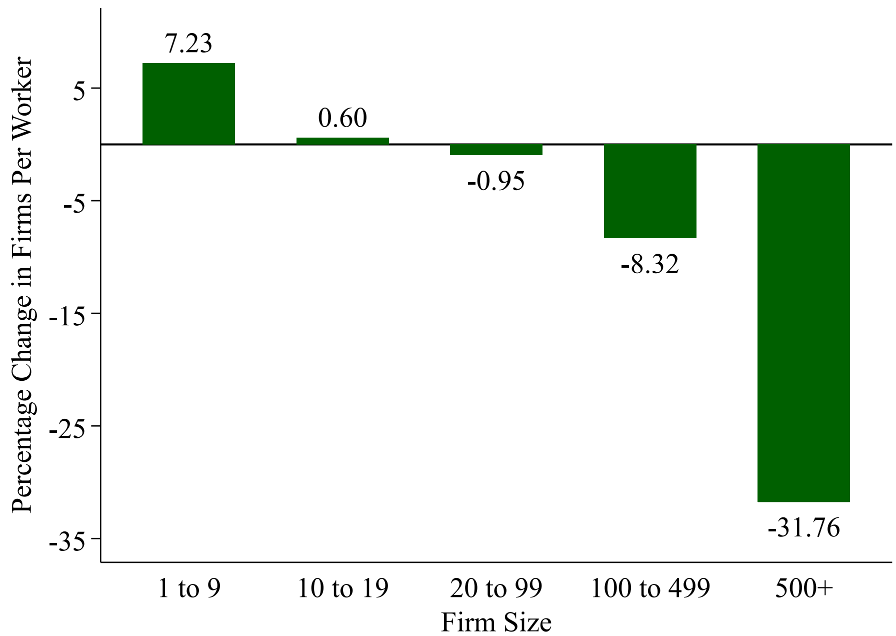
3.2.3 Quantitative Implications

I quantify the model's implications when the number of firms, holding constant all other model parameters, varies by the extent to which it has changed in the data between 1985-2017. Specifically, I undertake three experiments: (1) Simulate a change in the firm share over the job ladder over time. (2) Simulate a 13.1% decrease from the 1980s to 2010s in the number of firms at each productivity level. (3) Simulate an asymmetric change in the number of firms over the productivity distribution. I describe each of these below.

I. Changing the distribution of firms over the job ladder: A key ingredient of the model is the distribution of firms over the job ladder. Few large firms at the top of the job ladder amplify the mega-firm and retaliation channels. The baseline calibration of the model approximated the firm distribution over productivity levels by the share of firms over firm size classes, conditioning on firm age and sector. Figure 4 plots the distribution of firms over the firm size ladder in the baseline model for the period of 1987-89. It also superimposes the corresponding distribution for 2015-17. Note that over time, the firm share distribution has shifted to the left, and the magnitude of this decline has been almost 13 percent in the firm sizes classes above 20 employees. In each of the experiments, I change the distribution of firms over the job ladder as depicted in Figure 4.

II. Decreasing firms per worker uniformly over the job ladder: The US economy

Figure 5: Firms per Worker over Firm Size Bins, Changes in 2015-17 relative to 1987-89



Notes: This figure shows the changes from 2015-17 to 1987-89 in the long-run average of the ratio of the number of firms to workers over firm size classes, using the Business Dynamics Statistics.

displayed a 13.1 percent decline in the number of firms per worker between the 1980s and the 2010s. In the next experiment, I simulate a decline in the firms per worker in the model to the same extent that is observed in the data. Specifically, I decrease the number of firms by the same fraction at each productivity level, holding the number of workers fixed.

III. Changing firms per worker asymmetrically over the job ladder: Finally, I explore the evolution in firms per worker differentially over the firm size ladder. Figure 5 plots changes in the employment-weighted average firms per worker between 1987-89 and 2015-17 for the five firm size bins from the BDS, conditional on firm age and sector. Between the two time periods, small-sized firms saw an increase in the average number of firms per worker, whereas most of the aggregate decline resulted from large-sized firms. This happened because the growth rate of employees outpaced the growth rate of firms among the largest firm size classes. In other words, the firm size distribution became increasingly dispersed over time.[17] I utilize the asymmetric nature of changes in firms per worker across different firm size classes by varying, differentially, the number of firms in each tier of the job ladder by the extent to which it has changed in the corresponding size class in Figure 5. This translates to a decline in firms at the upper rungs of the job ladder and an

[17]Please see section 4.2 for a discussion on this.

increase in the lower ones.

Table (3) reports the actual changes in the data and the model implied response for EE transitions and Wages/Productivity to each of the aforementioned variations of the number of firms. Panel (a) compares the average EE transitions rate and the real hourly compensation/real hourly output for the US economy in 1985-90 and 2012-17. For both periods, the long-run averages of the two moments have been computed from the CPS and BLS, respectively.[18] Panel (b) first simulates the change in firm distribution over the job ladder shown in Figure (4). The model can account for about 17 percent of the decrease in EE rate and a small fraction of the decrease in wages. Further decreasing the firms per worker uniformly at each productivity level results in a decline in EE transitions of 6.2 percent, accounting for about a third of the overall decrease over the two periods. Wages/productivity declines by 0.6 percent, accounting for about seven percent of the overall decrease in the data. Finally, the last panel shows that simulating a disproportionate change in the number of firms in the model corresponding to Figure 5 further exacerbates the decline in the two moments. The model now explains more than two-thirds of the overall decline in EE transitions and about 19 percent of the decrease in wages relative to productivity.

This section showed the qualitative and quantitative predictions of the model when the number of firms varies, holding the number of workers and all other parameters fixed. The comparative statics point to a direction of decline in EE transitions and wages/productivity in response to decreasing competition. In terms of magnitudes, the model can account for 1/3th - 2/3rd of the decline in EE transitions and 3-19 percent of the decrease in wages. Overall, the model presented in the last section hinges on the finiteness of firms as a source of their market power. Empirically, this translates to changes in the number of employing firms in a labor market with a given number of workers. The model predicts that markets with a higher number of firms would result in more outside options for workers. More outside options have twofold implications for employed workers. First, more chances for workers to quit their firms, resulting in a high rate of job-to-job transitions. Second, increased efforts of firms to retain workers, resulting in higher average wages. In the next section, I attempt to empirically examine these model predictions and provide suggestive evidence of the model's implications.

[18] I use the EE transitions probability series provided by Fujita, Moscarini & Postel-Vinay (2022), which is based on the imputation of missing answers to questions that affect the computation of EE transitions post-2008 in the CPS. For wages/productivity, I deflate both series by the implicit price deflator to alleviate concerns about its downward trend being driven by differences in price deflators typically used for computing real compensation (CPI-urban) and output (implicit price deflator).

Table 3: Data and Model-generated Moments (Non-Targeted)

	EE transitions Rate (%)	Wages/Productivity
	(a) Data	
1985 - 1990	2.83	1.00
2012 - 2017	2.29	0.90
Actual change, %	-18.9	-9.76
	(b) Model	
I. Changing distribution of firms over the job ladder		
Model change, %	-3.23	-0.31
Explained by model, %	17.1	3.18
II. 13.1 percent symmetric decrease in firms per worker		
Model change, %	-6.16	-0.64
Explained by model, %	32.6	6.56
III. Asymmetric change in firms per worker		
Model change, %	-13.8	-1.84
Explained by model, %	73.0	18.8

Notes: This table evaluates the model-simulated moments in 1985-90 (1980s) against their empirical counterparts measured in 2012-17 (2010s). Change refers to the percentage change in the long-run average of the moment from 1985-90 to 2012-17. Panel (a) shows (i) average employment-to-employment flows measured at a monthly frequency and averaged over a five-year horizon from the CPS, and (ii) the five-year average of real compensation per hour index/real output per hour index, denoted at w/p, and normalized to 1 in the 1980s, from the BLS. Panel (b, I) simulates the change in firm distribution over the job ladder shown in Figure (4). Panel (b, II) decreases firms per worker by 13.1 percent in the model, and Panel (b, III) simulates changes in firms per worker in each productivity bin corresponding to Figure (5). Each experiment reports the corresponding changes in the two moments and the fraction of their decrease in the data that is accounted for by the model.

4 Firms Per Worker and Model Outcomes in the Cross-Section

In this section, I first document empirical trends in the model-relevant measure of employer competition for workers − the number of firms in a labor market, normalized by the number of workers.[19][20] As the number of firms, along with the number of workers, in the US economy has trended upwards over the last several decades, I use the ratio of the two as a measure of labor market competition. I document evidence of a persistent and long-run decline in the number of firms per worker in the US, starting from the early

[19]More precisely, the empirical counterpart of the measure of competition in the model is the number of hiring firms. This measure is not available over a long time horizon for the US economy. I proxy for this measure by the number of employer firms (i.e., excluding non-employee firms) available from the late 1970s.

[20]Workers specifically refer to employed workers. I focus on employed workers because of the availability of their data in narrowly-defined markets. The aggregate downward trend in firms per worker shown in the next section has been similarly observed for firms per working-age person and firms per labor force participant from the early 1990s.

1980s. I show that this decline is pervasive across two-digit industrial sectors, states, and sector-state pairs, and therefore, not a consequence of the compositional changes that have taken place over the same period in the US economy.

Next, I test the model's predictions by examining the relation between firms per worker and the different model-relevant outcomes in the data, such as the pace of job mobility, wages/productivity, wage growth associated with EE transitions, and the wage growth of job stayers. The aim is to provide descriptive evidence of the model's mechanism linking declining worker mobility and slowing wages in the US economy to the declining number of firms relative to workers.

Before presenting the empirical evidence on the model-relevant measure of competition and outcomes described above, I discuss the data sources in the next section.

4.1 Data

I use data from several sources to measure the effect of the number of firms per worker on the pace of worker mobility, average wages, and wage growth. First, I use publicly available tabulations from Business Dynamics Statistics (BDS). The BDS is part of the Longitudinal Business Database (LBD) of the US Census Bureau. It covers approximately 98 percent of non-farm private-sector employer businesses in the US starting 1978. It contains information on stocks of firms, establishments, and employees, as of March 12 of each year, disaggregated by location and industry. An establishment is identified by its physical location where a business is conducted, whereas a firm is an organization consisting of one or more establishments under common ownership or control. Employees consist of those working full- and part-time on a payroll.

Second, I link the BDS data with worker mobility and wage tabulations made publicly available from the Longitudinal Employer-Household Dynamics (LEHD) administrative data program. The LEHD is a matched employer-employee database of the US Census Bureau, and draws from data collected by state unemployment insurance programs. The data covers approximately 95% of all private sector employment, as well as employment in state and local governments. The public tabulations provide quarterly counts and rates of job-to-job transitions. Like the BDS, disaggregated data is available by region and industry. Still, unlike the BDS, all states did not enter the LEHD program simultaneously, with the earliest states' data available starting from 2000.

To combine data from the BDS and LEHD with measures of worker and firm demographics, I use local labor market statistics from the Quarterly Workforce Indicators (QWI). The QWI is also sourced from the LEHD program, and the earliest states entered the sample in 1990. QWI provides data on the composition of the workforce by age, education, firm age, and firm size and is disaggregated by locations and industries.

Combining the three data sources described above yields an annual panel over the sample period 2000-2018, with states entering the data at different times. The main variables of interest are measures of firms per worker, job-to-job flows, and employment composition by worker-age and education groups and firm-age and size groups. The combined dataset loses narrower levels of sectoral disaggregation that are available in some of the original sources. The most disaggregated data is available at the sector (two-digit NAICS industry) by MSA by year level. The overall dataset consists of an unbalanced panel of 381 MSAs, 18 industries over 19 years, yielding 124,750 sector-MSA-year observations.

To assess the model implied behavior of wages relative to productivity, I combine data on firms per worker with the annual payroll share of gross value added. I use the data from the BLS at the disaggregated-industry level from 1987. The payroll share of value added is a measure of labor share published by the Bureau of Labor Statistics (BLS). Labor income is expressed as the sum of the compensation to employees on payroll and the compensation of the self-employed, and I focus on the former component.[21] The dataset contains a panel of about sixty industries.

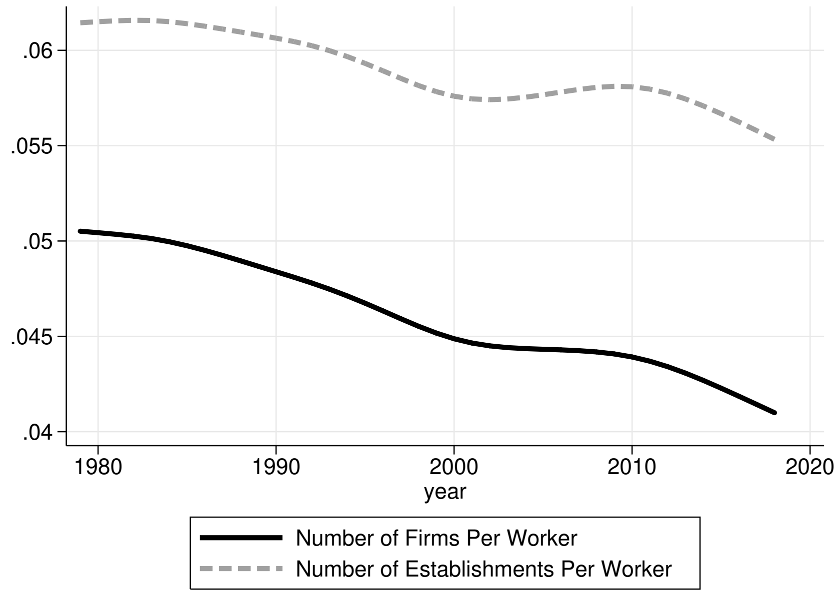
To measure residual wage growth associated with job switches and job stays, I use micro-data from the Survey of Income and Program Participation (SIPP) covering the period 1996-2000. The SIPP is a tri-annually collected, representative panel survey administered by the US Census Bureau, providing up 12 waves of individual data in the 1996 panel. Following Fujita & Moscarini (2017) I identify a primary job for each individual and define job spells and EE switches using job IDs and start and end dates of primary jobs. I merge the monthly SIPP data to firms per worker from the BDS at the state, sector, and year levels. For the main analysis, I consider the behavior of monthly wage growth for hourly workers and monthly earnings growth for non-hourly workers. Overall, the dataset contains about 50 thousand individual-1-year job spells and about 30 thousand instances of job-to-job transitions.

4.2 Evolution of Firms per Worker in the US Economy

I first focus on the number of firms, establishments, and workers for the aggregate US economy. Figure (6) plots trends in firms- and establishments- per worker from 1979-2018. Two observations are immediately apparent. First, both ratios experienced a long-run decline over the sample period, with firms per worker recording a steeper decline (18.3%)

[21] Elsby et al. (2013) provide a detailed account of each component of labor share, including its measurement and constituents.

Figure 6: Firms and Establishments per Worker, 1979-2018



Notes: This figure shows the HP-filtered trends of the ratio of the number of firms and establishments to the number of workers in the US economy, over 1979-2018 using the Business Dynamics Statistics.

than establishments per worker (9.8%). While both ratios were roughly stable in the early 80s, they started experiencing a decline by the late 80s, which became more pronounced through the 90s. The 2000s saw a mild recovery, following a sharp decline in the years post the Great Recession.[22] Second, the declines were especially sharp in periods of economic boom, suggesting that growth in employers failed to keep pace with the growth in employees. In the analysis to follow, I focus on firms rather than establishments, as I am interested in the changing number of employers rather than the number of work locations of existing employers.

One possible interpretation of the aggregate decline in the firms per worker could be the compositional shifts across sectors or regions over the sample period. If labor is reallocated towards sectors or regions with a relatively low firm-to-worker ratio, then such reallocation could bias the aggregate ratio to lower values, even with unchanged or increasing firms per worker within those sectors or regions. This would raise the concern that the aggregate decline results from changing employment composition across industries and regions rather than a decline within them. To understand the role of compositional changes that have taken place over the sample period in driving the aggregate trend,

[22]It is noteworthy that the period from the late 1990s has also witnessed a secular decline in firm competition measured by concentration indices (such as employment-based Herfindahl-Hirschman index or employment share of the largest 20 firms in an industry (Autor, Dorn, Katz, Patterson & Van Reenen 2020) and wage markdowns (Yeh, Macaluso & Hershbein 2022). I show these trends in the next section.

Table 4: Firms per Worker by sector and time-period, 1984-2018

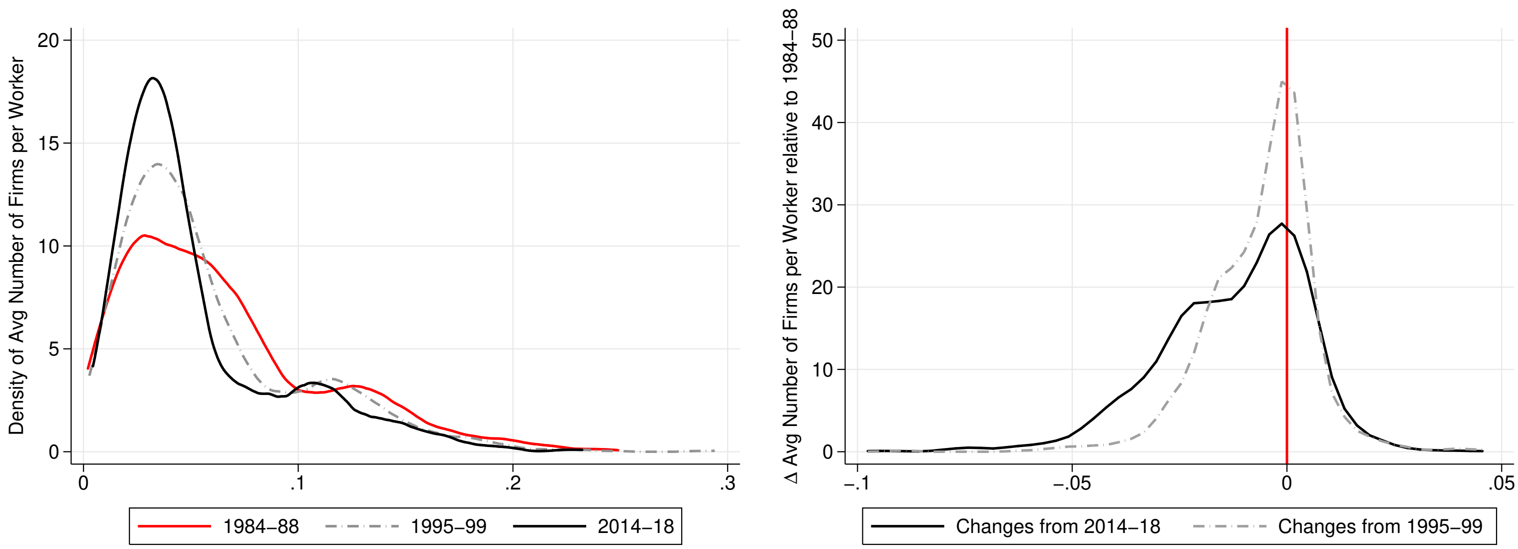
	1984-88	**1995-99**	**2014-18**
Mining (21)	0.038	0.041	0.031
Utilities (22)	0.008	0.010	0.010
Construction (23)	0.098	0.103	0.094
Manufacturing (31-33)	0.018	0.019	0.022
Wholesale Trade (42)	0.067	0.063	0.051
Retail Trade (44-45)	0.065	0.050	0.039
Trans & Warehousing (48-49)	0.040	0.038	0.036
Information (51)	0.021	0.022	0.022
Financial Activities (52-53)	0.057	0.057	0.058
Prof & business serv (54-56)	0.058	0.052	0.045
Edu & health (61-62)	0.045	0.036	0.030
Leisure & Hosp (71-72)	0.047	0.041	0.036
Other serv (81)	0.132	0.122	0.117

Notes: This table displays the long-run averages of firms to worker ratio for each sector, using the Business Dynamics Statistics. Two-digit NAICS sectors are listed in parenthesis.

I examine changes in firms per worker within sectors, regions, and sector-by-region cells.

Table (4) reports long-run averages of firms per worker within sectors, or two-digit NAICS industries, over five-year horizons. A few observations are noteworthy. First, the table shows that the shrinking sectors of the economy such as Manufacturing and Utilities had the lowest firms per worker in the 80s, and they were the only sectors that saw an increase in the ratio over time. A closer inspection into the trends in the levels of firms and workers plotted in Figure (A2) in the Appendix reveals that the decline in firms could not keep pace with labor reallocating away from these sectors. As a result, these sectors experienced an overall increase in the firms per worker over the sample period. Second, service sectors as Wholesale and Retail trade, which have grown over the last three decades, experienced a decline in firms, even as workers have increased. This led to an overall decrease in firms per worker. Finally, for the remaining services sectors, the number of firms increased but did not keep pace with the increase in employment, leading to an overall decline in the ratio. Overall, all services sectors of the economy experienced a drop in the firm-to-worker ratio, except Information and Finance which did not experience much change. I conclude that the aggregate decline in Figure (6) was not a result of compositional changes across sectors over the same period. In fact, Table (4) shows the opposite: sectors with the highest firms per worker in the 1980s US economy have expanded, while those with lowest firms per worker have contracted. The aggregate decline in firms per

Figure 7: Firms per Worker by state-sector pairs and time-period, 1984-2018



(a) Density of firms per worker

(b) Density of change in firms per worker relative to 1984-88

Notes: Panel (a) plots the density of long-run averages of firms per worker across state × two-digit NAICS sector pairs for three time-periods. Panel (b) plots the change in density of each time period of Panel (a) relative to 1884-88 (denoted by the red line at zero). The distributions are truncated at -0.1 and 0.05. Both panels use data for the US economy from the Business Dynamics Statistics.

worker was also not a result of shifting employment composition across different regions. Figure (A1) in the Appendix plots the firms to worker ratio for all states over the sample period and shows the decline is pervasive across all states.

To understand the evolution of the ratio within both states and sectors, Figure (7) panel (a) plots the distributions of long-run averages of firms per worker across state-by-sector cells for different periods. Note that in each subsequent sub-period starting from 1984-88 to 2014-18, the distribution of firms per worker has shifted towards zero, with a higher mass on lower values. Panel (b) plots the distributions of panel (a) expressed in terms of changes relative to their counterparts in 1984-88, denoted by the vertical line at zero. Panel (b) shows that the mass on negative values has increased – and that on positive values has declined – in each subsequent sub-period from 1984-88. Approximately 73% of the state-by-sector cells experienced a decline in firms per worker in 2014-18 relative to 1984-88. Furthermore, the mass on high negative values has increased over time, indicating a decline in the average firms per worker relative to 1984-88.

4.2.1 Firms Per Worker and Concentration Indices

How do firms per worker compare to other measures of firm competition? Figure 8 plots the Herfindahl–Hirschman Index (HHI) of employment concentration for several sectors of the economy (Autor et al. 2020) on the left axis, along with their firms per worker on the right axis. Both measures are computed by taking weighted averages of the corresponding ratios at the 4-digit industry level. The HHI takes each sector's sales/revenue share as weight, whereas firms per worker use the employment-based weights. The figure shows a clear negative relationship between the two measures for three major super-sectors in the US: Manufacturing, Services, and Trade. Similar trends are also observed in the correlation of firms per worker, and the employment shares of the largest firms across industries, also reported in (Autor et al. 2020).

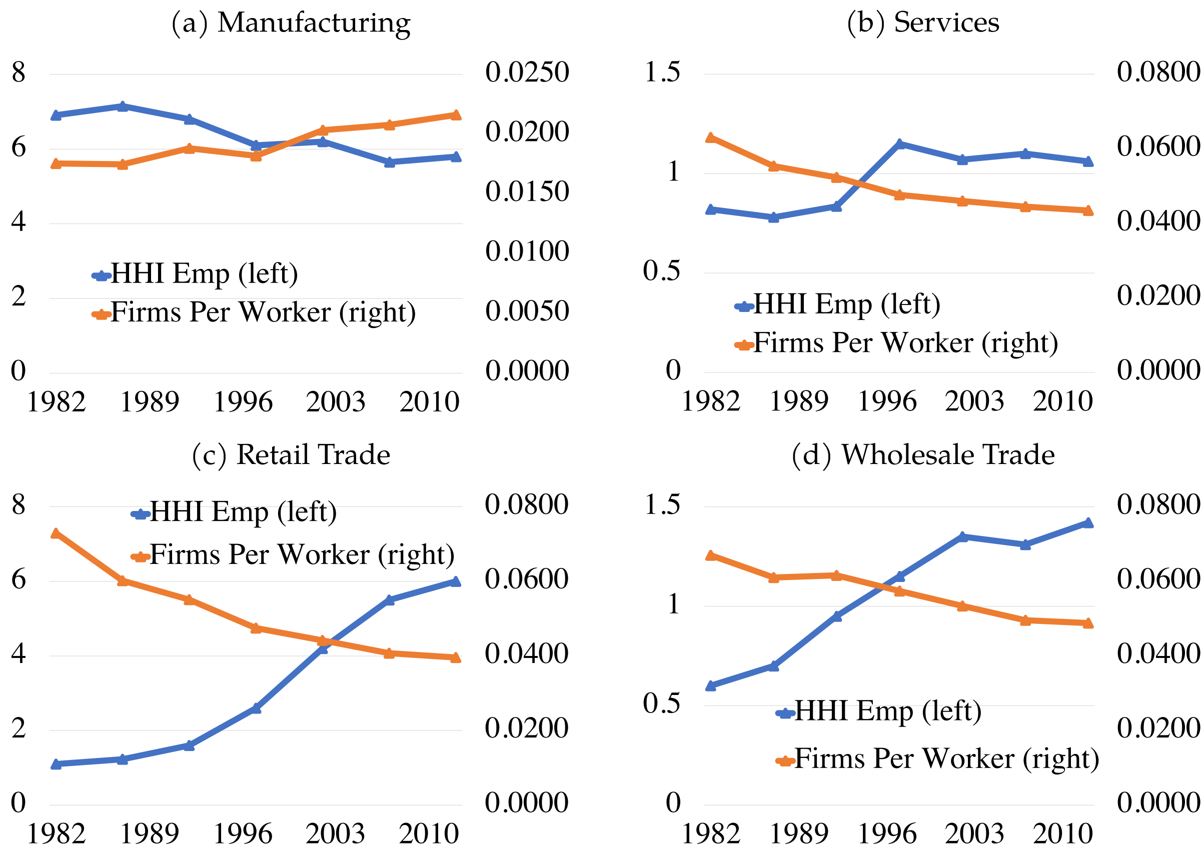
Next, Figure 9(a) plots firms per worker and sales-based HHI across all six-digit industries in the Economic Census of 2017. The relationship between the two measures is negative and robust: a one percent increase in firms per worker is associated with a 0.75 percent decrease increase in sales-based HHI. Figure 9(b) compares firms per worker with the employment share of the four largest firms across six-digit industries and finds a strong negative relationship.

To sum, the decline in the number of firms per worker is evident in the aggregate economy and within sectors, states, and a majority of sector-by-state cells. Firms per worker also behave consistently with measures of concentration. The strong correlation between firms per worker and conventionally used measures of competition makes the former especially appealing due to its public availability and detailed measurability across space and time. In the next section, I explore the relation between firms per worker and certain predictions of the model in the cross-section. I show that the decline in firms per worker is correlated to the pace of job mobility, average wages, and wage growth of job stayers and movers, in line with the model's predictions.

4.3 Assessing the Model's Implications in the Cross-section

The model presented in the last section predicts that firms per worker vary positively with (1) job-to-job transitions, (2) wages/productivity, and (3) wage growth of job stayers and negatively with (4) wage growth of job switchers. In this section, I test the model's implications pertaining to these moments using cross-sectional data. Appendix Figure (A3) shows that scatter plots of raw data summarizing these relationships are consistent with the model's predictions. Panel A3a plots the average EE transitions rate and firms per worker of US state-sector pairs in 2012-17 and shows that sub-markets with higher

Figure 8: Employment-based HHI from Autor et al. (2020) and Firms Per Worker



Notes: This figure displays the employment-based average HHI (Autor et al. 2020) and Firms per Worker within four-digit industries. Both indices are averaged across all four-digit industries to arrive at sector aggregates. The HHI and firms per worker, respectively, weigh industries by their share of total sales and total employees.

firms per worker also had a higher EE transitions rate. Panel A3b plots the employment-weighted payroll share of value added with the firms per worker across industries in 2012-17 and shows a positive relationship between the two. Panels A3c and A3d show binned scatter plots of, respectively, individual wage growth across 12-month job spells with the same employer, and wage growth associated with EE transitions plotted against the firms per worker belonging to the state and sector of the individual between 1996-2000. Job stayers in markets with higher firms per worker experienced higher annual wage growth, and job switchers who moved from markets with higher firms per worker experienced lower wage growth. In the following sections, I explore these relationships formally in the data.

Figure 9: Sales-based HHI, Employment Concentration and Firms Per Worker

(a) Sales-based HHI and FPW

(b) Employment-share of Top 4 firms and FPW

Notes: Economic Census, 2017. This figure displays binned-scatter plots of firms per worker and (a) sales-based HHI, and (b) employment-share of top 4 firms across six-digit industries. The top 4 firms are defined on the basis of sales.

4.3.1 Firms Per Worker and EE Transitions

The decline in labor market dynamism has been well-documented for the US economy (Hyatt & Spletzer 2016, Molloy, Trezzi, Smith & Wozniak 2016), and is particularly evident on the worker-side from the declining pace of job-to-job transitions. This section provides evidence of the association between job-to-job flows and the firm-to-worker ratio. The reduced-form specification is the following:

$$log(EE\ Rate)_{jmt} = \beta_1 log(Firms\ Per\ Worker)_{jmt} + \beta_2 X_{jmt} + \alpha_{jt} + \alpha_{mt} + \epsilon_{jmt} \qquad (12)$$

where $log(EE\ Rate)_{jmt}$ is the log of average job-to-job transition rates in sector j, MSA m, and in year t. The main explanatory variable $log(Firms\ Per\ Worker)$ is the log of the firm to worker ratio; X is the share of the workforce by their age (14-18, 19-21, 22-24, 25-34, 35-44, 45-54, 44-64, 65+), and education groups (below high school, high school, college, above college), as well as the share of workforce at firms of different age- (0-1, 2-3, 4-5, 6-10, 11+) and size-groups (0-19, 20-49, 50-249, 250-499, 500+ employees) at the sector-metropolitan area-year level. α_{jt} is a vector of sector-by-year fixed effects, and α_{mt} is a vector of metropolitan area-by-year fixed effects. Thus, the relation between firms per worker and EE rate utilizes the variation across local labor markets, denoted by metropoli-

Table 5: OLS Regressions of Employer-to-Employer Transitions Rate on Number of Firms per Worker

	Log EE Rate		
	(1)	(2)	(3)
Log Firms per Worker	0.084***	0.099***	0.106***
	(0.016)	(0.017)	(0.017)
MSA-Year FE		✓	✓
Sector-Year FE			✓
Observations	69867	69819	69819
R^2	0.94	0.95	0.96

Notes: This table displays regressions of job mobility on the number of firms per worker in each column. The dependent variables are logs of the Employer-to-Employer Separations Rate. All regressions control for MSA, year, and sector FEs as well as the full set of controls, including the fraction of workforce in each sector-MSA-year cell belonging to different age, education, firm age, and firm size groups. All MSA-sector cells are employment-weighted. Columns (2) further includes MSA x year fixed effects, and columns (3) additionally includes Sector x year fixed effects. Sectors are defined as two-digit NAICS industries. SEs clustered at MSA x Sector level in parenthesis. Sample trimmed at 5 and 95 percentiles. Source: BDS, QWI, and Job-to-Job (J2J) flows data by the LEHD, 2000-2017. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

tan area-sector pairs, controlling for time-varying characteristics of sectors and metropolitan areas.[23] All standard errors are clustered at the metropolitan area-by-sector level and sub-markets are employment-weighted.

Table (5) columns (1)-(3) report the coefficient on log firms per worker from estimating different specifications of equation (12), where the dependent variable is the EE separations rate. Overall, the number of firms per worker is positively related to the EE transitions rate. When the specification is run with all controls and MSA, year, and sector fixed effects (specification 1), a one-log point increase in firms per worker is associated with an increase of about 0.084 log points in the EE transitions rate. Further, allowing MSA-specific characteristics to vary over time (specification 2) increases the correlation between the two variables to 0.099. Additionally, introducing sector-year fixed effects (specification 3) keeps the coefficient nearly stable. Overall, table (5) suggests EE transitions rates are higher in markets, defined as MSA-sector pairs, with more firms per worker. As a robustness check, Table (A2) regresses log EE transition counts on log firms and log workers using the same specifications. I find coefficients related to firms and workers to be posi-

[23] I do not use time-series differences within local labor markets to identify the relation between firms per worker and labor flows because of the relatively small time length of the sample, which is confounded by the Great Recession. The majority of states enter the sample post-2004, and the annual dataset from 2004-18, ignoring the effects of 2008-12, does not offer enough variation. I , therefore, utilize cross-sectional variation.

Table 6: OLS Regressions of Payroll of Value Added on Number of Firms per Worker

	Log Payroll Share of Value Added			
	(1)	(2)	(3)	(4)
Log Firms per Worker	0.027*	0.026*	0.045***	0.041**
	(0.016)	(0.016)	(0.017)	(0.018)
Year FE		✓	✓	✓
Sector FE			✓	✓
Sector-Year FE				✓
Observations	1753	1753	1753	1648
R^2	0.002	0.029	0.226	0.182

Notes: This table displays regressions of log payroll share of value added on the log number of firms per worker in each column. Column (1) shows the raw correlation coefficient. Columns (2)-(4) successively add controls for year, 11 sectors, and year-sector fixed effects. The sample is at the year-industry level from 1987-2019 for 58 industries defined at the two- and three-digit NAICS level. Robust SEs in parenthesis. Sample trimmed at 5 and 95 percentiles. Source: Bureau of Economic Analysis, 1987-2019. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

tive and significant, with log firms being of a higher magnitude.[24]

To sum, this section shows a positive association between firms per worker and job-to-job flows, and these results are robust when controlling for time-varying characteristics of metropolitan areas and sectors, as well as employment composition across worker and firm demographic groups at the MSA-by-sector level. Insofar as the number of firms reflects employer competition across local labor markets, these results are indicative of the model's implications for the decline in labor market dynamism being driven by decreasing the number of firms per worker.

4.3.2 Firms Per Worker and Payroll Share of Value Added

The model presented in the last section showed that wages relative to productivity are positively related to the number of firms per worker. As the labor market becomes more crowded with firms, the outside options of the worker improve. The retaliation channel has less bite, which increases the option value of search and, therefore, the worker's share of the match. Thus, workers facing a higher number of firms realize a higher average wage level for a given level of productivity.

In this section, I document a positive relation between firms per worker and the com-

[24] I also run the same specification using job-to-job hires rates and find that it is positively correlated with firms per worker across all specifications shown above. The results of this robustness exercise are omitted.

pensation to payroll employees as a fraction of the gross value added. This ratio can be expressed as:

$$\text{Payroll Share of Value Added} = \frac{\text{Average hourly compensation to payroll employees} \times \text{Hours worked}}{\text{Quantity produced}}$$

where the average hourly compensation includes wages and salaries to employees on payroll along with employer contributions to pension and insurance funds. To the best of my knowledge, this is the only measure of wages/productivity available at a disaggregated industry level. I utilize the cross-industry dispersion and specify the following:

$$log(Wages/Productivity)_{jkt} = \beta \cdot log(Firms\ Per\ Worker)_{jkt} + \alpha_k + \alpha_t + \epsilon_{jkt} \qquad (13)$$

where $log(Wages/Productivity)_{jkt}$ is the log of payroll share of value added in 58 industries (j) expressed at the two- and three-digit levels, in eleven sectors-k for 32 years (t), from 1988-2019. The main explanatory variable is the log of firms per worker at the industry-sector-year level, and α_k and α_t are, respectively, sector and year fixed effects.

Table (6) reports the elasticity of wages/productivity to firms per worker. Specification (1) shows the raw correlation coefficient, whereas specifications (2)-(4) successively control for a year, eleven 2-digit sectors, and year-sector fixed effects. The variation in the last column utilizes differences across disaggregated industries and industry-years, within a broader sector and year. It also controls for time-varying characteristics of the sector to which the industries belong. The regression coefficient remains positive across all specifications, showing that the number of firms per worker positively relates to wages/productivity. Specification (1) shows that a one-log point increase in firms per worker is associated with an increase of about 0.027 log points in the payroll share. Further, controlling for fixed differences across sectors and year-by-sectors nearly doubles the correlation between the two variables to 0.041-0.045 in specifications (3) and (4).

To sum, the table shows that labor markets, defined as disaggregated industries, with more firms per worker, also see a higher payroll share of value added.

4.3.3 Firms Per Worker and Wage Growth of Job Switchers and Stayers

The model presented in the last section predicts that wage growth associated with EE transitions is negatively related, while that associated with continuous job spells is positively related to the number of firms per worker. As the workers' labor market becomes populated with an increasing number of firms, they become more likely to receive outside offers through on-the-job search. In such a setting, workers receiving more offers on

Table 7: OLS Regressions of Wage Growth associated with J2J transitions on Number of Firms per Worker

	(a) Wage Growth | Job Switchers		(b) Wage Growth | Job Stayers	
	Hourly Worker (1)	Monthly Earnings (2)	Hourly Wages (3)	Monthly Earnings (4)
Log (Firms Per Worker)	-0.0112**	-0.0291**	0.0006	0.0084**
	(0.00461)	(0.0142)	(0.0010)	(0.0039)
State FE	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓
Year Month FE	✓	✓	✓	✓
Observations	18113	7918	26845	20010
R^2	0.024	0.041	0.424	0.336

Notes: This table displays regressions of wage growth associated with job-to-job transitions and 12-month employment spells on the number of firms per worker. In Panel (a), the dependent variables are the month-over-month change in the log of the hourly wage rate for hourly workers (Column 1) and earnings for non-hourly workers (Column 2). The sample pertains to workers making EE transitions. In Panel (b), the dependent variables are the annual changes in the log of the hourly wage rate for hourly workers (Column 3), and earnings for non-hourly workers (Column 4). The sample pertains to workers with a continuous 12-month employment spell with the same employer. All regressions control for a vector of worker and job-specific characteristics, including dummies for age, squared age, education, race, and gender of the worker, and whether the employer is in the public sector, the occupation and unionization status of the job. Panel (a) includes controls pertaining to the worker's separating sector, while Panel (b) includes controls pertaining to the worker's current sector. Panel (b) further controls for worker fixed effects. SEs clustered at State x Sector level in parenthesis. Sample trimmed at 5 and 95 percentiles. Source: Survey of Income and Program Participation, 1996-2000 (1996 Panel). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

the job realize higher levels of wages (and potentially max out on wages in the model) as job stayers. Thus, when they transition from one job to another, they realize lower gains associated with those moves. This leads wage growth realized through job switches to be negatively related to firms per worker. In this section, I document these model-implied relationships in the 1996 panel data from the SIPP. The reduced form specification is the following:

$$\Delta log(w)^k_{ijst} = \beta_1 log(\textit{Firms Per Worker})_{jst} + \beta_2 X_{it} + \alpha_j + \alpha_s + \alpha_t + \epsilon_{ijst} \tag{14}$$

where $\Delta log(w)^k_{ijst}$ is the change in the log of (1) wages paid to hourly workers, and (2) earnings paid to non-hourly workers, both deflated by the Consumer Price Index-Urban. The subscripts i denotes individual, t, the calendar-month, j, the sector, s, the state, and superscript $k \in \{\text{Stayer}, \text{Switcher}\}$ distinguishes between a job-switcher and a job stayer continuously employed over a year. $\Delta log(w)$ is computed month-over-month for job switchers, and over a year for job-stayers. The sample is restricted to workers making EE transitions or completing at least one 12-month employment spell with the same employer. The primary explanatory variable, $log(\textit{Firms Per Worker})$ is the firms per worker defined for state-s and two-digit sector-j.[25] X_{it} is a vector of worker and job-specific characteristics, including dummies for age, squared age, education, race, and gender of the worker, and whether the employer is in the public sector, the occupation and unionization status of the job to control for composition effects. α_j, α_s and α_t denote sector, state and calendar-month effects. For job switchers, the right-hand side variables are associated with the job at month $t-1$, i.e., pertaining to the job that the worker is separating from while making the EE transition. The results remain robust if I instead benchmark the right-hand side variables to the job the worker is getting hired to. The regressions for job stayers additionally include person-fixed effects. I use person-weights, restrict the sample to 16-65-year-old individuals, and cluster standard errors at the state-by-sector level.

Table (7) Panel (a) presents the regression results for job switchers. Columns (1) and (2) show that a ten percent increase in firm per worker is associated with a 0.1 percentage point decrease in wage growth and a 0.3 percentage point decrease in the earnings growth associated with job-to-job transitions. Panel(b) reports the results for job stayers. Columns (3) and (4) show that a ten percent increase in firms per worker is associated with a 0.08 percentage point increase in earnings growth of job stayers and a negligible increase in

[25]The time convention I follow in assigning annually observed BDS data to monthly SIPP data follows Moscarini & Postel-Vinay (2012). I assign year t, April to year t+1, March observations of the SIPP to firms and workers of year t+1. This is because BDS observations are reported in mid-March of each year and are assumed to reflect the labor market of the previous year.

the wage growth of hourly workers. Overall, I find support for the idea that workers in markets with higher firms per worker realize a smaller wage growth as job switchers and higher ones as stayers.

4.3.4 Supporting Evidence

Firms Per Worker and Average Wages

In this section, I supplement the wage level regressions pertaining to the payroll share of value added by using data from the LEHD that is disaggregated at a narrower level than the one from the BLS. I estimate the relation between firms per worker and the average wages of workers making various labor market transitions using the following specification:

$$\mathit{log}(\mathit{wages})_{jmt} = \beta_1 \mathit{log}(\mathit{Firms\ Per\ Worker})_{jmt} + \beta_2 X_{jmt} + \alpha_{jm} + \alpha_{mt} + \alpha_{jt} + \epsilon_{jmt} \tag{15}$$

where $log(wage)_{jmt}$ is the log of the average real wage of workers making job-to-job, nonemployment to employment, and employment to nonemployment transitions in sector-j, MSA-m, and year-t. The main variable of interest $log(FirmsPerWorker)$ is as before, and control variables include workforce composition of a metropolitan area-sector-year cell in various firm-size and age groups.[26] α_{jm} is a vector of sector-by-MSA (market) level fixed effects, to control for fixed differences across markets. α_{jt} is a vector of time-varying sector effects to control for sector-specific shocks. I add MSA-by-year fixed effects, α_{mt}, to control for the time-varying effects of state-determined minimum wage and unemployment insurance programs that are expected to drive some variation in wages. Finally, wages are deflated by Consumer Price Index-Urban and MSA- and MSA-by-year fixed effects absorb fixed and time-varying price differences across metropolitan areas. All standard errors are clustered at the metropolitan area-by-sector level.

The variation in equation (15) stems from market-specific, time-varying differences in firms per worker. As pointed out in the literature, the key concern in interpreting the results of such an estimation is that certain market-specific and time-varying variables, such as productivity and local labor market tightness, are expected to affect wages and firms per worker. To alleviate this concern, and in the spirit of prior literature estimating the effect of Herfindahl-Hirschman Index (HHI) on wages in local labor markets (Azar, Marinescu & Steinbaum 2020, Marinescu et al. 2020), I instrument firms per worker in each sector-year-metropolitan area cell, with the average of log firms per worker for all other metropolitan areas for that sector and year.[27] This instrument captures the variation in firms per worker that is not driven by changes in a sector of any particular

[26] In line with literature studying the effect of employer concentration on average wages (Benmelech et al. 2020, Azar, Marinescu & Steinbaum 2020, Marinescu et al. 2020), I utilize time-series variation instead of the cross-sectional one. In a similar vein, I do not control for worker demographic composition, as it is not expected to affect average wage levels.

[27] The results of this section are robust to an alternative instrument that averages the log of firms per worker across MSAs in all other states for the same sector and year.

metropolitan area but rather by economy-wide changes in that sector. Thus, the instrument does not depend on either productivity or market tightness of the local metropolitan area, which are likely to be the two main time-varying, market-specific variables that are omitted in equation (15), and may confound the interpretation of the variable of interest. The main setback of using this instrument is that it is at the sector-year level. Thus, sector-specific shocks in the aggregate economy that could affect local wages cannot be controlled. With this caveat, I present the results of the various specifications of equation (15) below.

Table (8a) shows results from the baseline specification of average real wages of job-to-job hires regression on firms per worker. Specification (1) introduces year and market effects and shows a negative coefficient on log firms per worker. On adding employment share across various firm age and size groups in specification (2), the sign of the coefficient turns positive. This is an expected result because without firm-level controls, the firms to workers ratio, which is the inverse of the average firm size, captures the firm size wage premium, a well-documented fact in the literature.[28] Specifications (3) allows for time-varying MSA effect doubles the magnitude of the coefficient and retains its size and significance.

Specifications (4)-(6) are instrumental variable counterparts of specifications (1)-(3). The coefficient signs are positive and significant for all specifications, and their magnitudes are higher than the OLS estimates. Introducing controls for firm demographic composition increases the magnitude of the coefficient in specification (5) compared to (4) while further adding MSA-year fixed effects (specification 6) does not affect the coefficient. Depending on the specification, a 10% increase in firms per worker is associated with a 1.4%-3.2% increase in average wages of job-to-job hires. Appendix table (A1a) presents results from the first stage.

Next, tables (8b) and (8c) show the effect of firms per worker on wages of hires from and separations to non-employment, respectively. The preferred specification in column (3) examines variation within markets, controlling for MSA-specific shocks, and finds a positive coefficient for hires and separations. Instrumenting for the number of firms per worker and running the same specification in column (6) yields positive coefficients that are larger in magnitude than the OLS counterparts, much like the results in table (8a). A 10% increase in firms per worker is associated with a 1.5%-3.8% increase in wages of hires from non-employment, and a 1.3%-4% increase in the wages of separations to non-employment. Appendix tables (A1b) and (A1c) present results from the first stage of the IV regressions.

Overall, the results of this section are consistent with the predictions of the model. They suggest that for a given market size and firm size distribution, the number of firms in a market is positively associated with the average wages of workers making labor market transitions.

[28] A key outcome of the model by Burdett & Mortensen (1998) is that larger firms pay higher wages. This is documented robustly in the empirical literature, pioneered by Brown & Medoff (1989), and more recently in Bloom, Guvenen, Smith, Song & von Wachter (2018).

Table 8: OLS and Instrumental Variable Regressions of Wages on No. of Firms per Worker

(a) OLS & IV Regressions: Log (Wages of J2J Hires) on Log(Firms per Worker)

	OLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
Log Firms per Worker	-0.0223***	0.0111*	0.0262***	0.144***	0.324***	0.320***
	(0.00575)	(0.00644)	(0.00610)	(0.0241)	(0.0293)	(0.0270)
Firm controls		✓	✓		✓	✓
MSA-Year FE			✓			✓
Observations	98162	70277	70260	91944	67448	67431
R^2	0.839	0.930	0.942	0.855	0.922	0.936

(b) OLS & IV Regressions: Log (Wages of NE Hires) on Log(Firms per Worker)

	OLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
Log Firms per Worker	-0.0225***	-0.0126*	0.00996	0.150***	0.377***	0.379***
	(0.00586)	(0.00701)	(0.00695)	(0.0253)	(0.0362)	(0.0329)
Firm controls		✓	✓		✓	✓
MSA-Year FE			✓			✓
Observations	99251	69752	69736	92625	66907	66891
R^2	0.860	0.909	0.924	0.865	0.899	0.917

(c) OLS & IV Regressions: Log (Wages of EN Separations) on Log(Firms per Worker)

	OLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
Log Firms per Worker	-0.0273***	0.00107	0.0181***	0.130***	0.410***	0.408***
	(0.00556)	(0.00695)	(0.00681)	(0.0236)	(0.0355)	(0.0337)
Firm controls		✓	✓		✓	✓
MSA-Year FE			✓			✓
Observations	99837	69666	69649	93488	66836	66819
R^2	0.869	0.910	0.923	0.866	0.898	0.914

Notes: This table displays OLS and instrumental variable regressions of wages associated with labor market transitions on number of firms per worker. All specifications control for year and market (sector x MSA) fixed effects. Columns (1)-(3) of sub-tables (8a)-(8c) respectively, shows the OLS regression of log of wages associated with job to job hires (J2J), nonemployment-to-employment (NE) hires, and employment-to-nonemployment (EN) separations on log of firms per worker. The remaining columns show corresponding IV regressions, where log firms per worker is instrumented by the average of log firms per worker across all other MSAs in that sector and year. Sectors are defined as two-digit NAICS industries. Firm controls include the fraction of workforce in each cell belonging to different firm age, and firm size groups. SEs clustered at MSA x Sector level. Sample trimmed at 5 and 95 percentiles. Source: BDS, QWI and Job-to-Job (J2J) data by the LEHD. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5 Conclusion

Employer-to-employer transitions rate declined from the late 1990s to the 2010s in the US. Concurrently, real wages failed to keep pace with productivity. In this paper, I explore the role of firm market power in driving the decrease in worker mobility and wages. My measure of labor market power is the number of employers per worker, which is the inverse of the average firm size. I show that this ratio has decreased both in the aggregate US economy as well as in sub-markets defined by geographies and industries from the early 1980s, preceding the decline in worker mobility and wages.

I examine the link between firm competition, worker mobility, and wages in a search model of the labor market where an increase in employer market power restricts workers outside options through three main channels. First, as firms in a labor market shrink, holding the employees constant, each firm becomes larger. As employment and job offers get concentrated in large firms, workers in such firms face a reduction in the share of outside offers as they cannot access offers from their own firms. Second, firms can retaliate against potential employees by not allowing their applicants who reject their offers to re-apply to them. This reduces the applicant's value from searching outside of the firm. Third, the skewed distribution of firms along the productivity distribution gives rise to a small number of mega-firms at the top of the job ladder. As the number of firms per worker among mega-firms becomes even smaller over time, these firms amplify the effect of the two channels described above.

I calibrate the model to match the 1985-90 US economy and evaluate it against the 2012-17 period. The model can quantitatively account for about 2/3rd of the decrease in EE transitions and 1/5th of the decline in wages relative to productivity. I also find evidence of the model's implications across sub-markets characterized by states and sectors of the US: markets with a higher firm per worker are associated with a higher EE rate and payroll share as a fraction of gross value added.

This paper adds to the growing literature on the decline in labor market dynamism in the US. It offers a market-power-based explanation for declining worker mobility by examining a previously unexplored link between firms per worker and EE transitions. With the increased availability of micro-data from the US Census Bureau, a more thorough investigation of the degree of competition in a worker's relevant labor market, and how that affects measures of labor market dynamism is possible. The analysis presented in this paper abstracts from worker heterogeneity and how workers at various parts of the skill distribution are affected by changes in labor market competition. I leave that as an area of future research for this project. This paper takes a step towards understanding the link between two widely discussed and contended macroeconomic aggregates in the US economy - rising firm market power in labor markets and declining labor market dynamism - and explores its implications on wages.

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A Model Appendix

A.1 Nash Bargaining

Claim: Suppose an employed worker at firm-θ_i has an outside option at firm-θ_j. Then the Nash bargained wage, $\omega(\theta_i, \theta_j)$ solves equation (3).
Proof: Nash bargaining implies that the worker and firm negotiate a wage that solves the following objective function:

$$\begin{aligned}
&\max\Big(W(\theta_i, \omega(\theta_i, \theta_j)) - \widetilde{W}(\theta_j, \omega(\theta_j, \theta_j), \theta_i)\Big)^{\alpha}\Big(J(\theta_i, \omega(\theta_i, \theta_j))\Big)^{1-\alpha} \\
&= \max\Big[\alpha log\Big(W(\theta_i, \omega(\theta_i, \theta_j)) - \widetilde{W}(\theta_j, \omega(\theta_j, \theta_j), \theta_i)\Big) + (1-\alpha) log\Big(J(\theta_i, \omega(\theta_i, \theta_j))\Big)\Big]
\end{aligned}$$

where $\omega(\theta_j, \theta_j) = \theta_j$. First order condition w.r.t. $\omega(\theta_i, \theta_j)$:

$$\alpha \frac{W_\omega(\theta_i, \omega(\theta_i, \theta_j))}{W(\theta_i, \omega(\theta_i, \theta_j)) - \widetilde{W}(\theta_j, \omega(\theta_j, \theta_j), \theta_i)} = -(1-\alpha)\frac{J_\omega(\theta_i, \omega(\theta_i, \theta_j))}{J(\theta_i, \omega(\theta_i, \theta_j))}$$

Note that $W_\omega(\theta_i, \omega(\theta_i, \theta_j)) = -J_\omega(\theta_i, \omega(\theta_i, \theta_j))$ from the expressions of W and J in equations (5) & (9).

$$\begin{aligned}
\alpha J(\theta_i, \omega(\theta_i, \theta_j)) &= (1-\alpha)\Big(W(\theta_i, \omega(\theta_i, \theta_j)) - \widetilde{W}(\theta_j, \omega(\theta_j, \theta_j), \theta_i)\Big) \\
W(\theta_i, \omega(\theta_i, \theta_j)) &= \widetilde{W}(\theta_j, \omega(\theta_j, \theta_j), \theta_i) + \alpha\Big(W(\theta_i, \omega(\theta_i, \theta_j)) + J(\theta_i, \omega(\theta_i, \theta_j)) \\
&\quad - \widetilde{W}(\theta_j, \omega(\theta_j, \theta_j), \theta_i)\Big) \\
W(\theta_i, \omega(\theta_i, \theta_j)) &= \widetilde{W}(\theta_j, \omega(\theta_j, \theta_j), \theta_i) + \alpha\Big(V(\theta_i) - \widetilde{W}(\theta_j, \omega(\theta_j, \theta_j), \theta_i)\Big)
\end{aligned}$$

which simplifies to equation (3):

$$W(\theta_i, \theta_j) = \widetilde{W}(\theta_j, \theta_j, \theta_i) + \alpha\Big(V(\theta_i) - \widetilde{W}(\theta_j, \theta_j, \theta_i)\Big)$$

■

A.2 Solution Algorithm

The solution algorithm involves sequentially solving for θ_u, and $\widetilde{V}$ through value function iteration. I write the following algorithm to solve the model numerically:

While $\widetilde{V}' \neq \widetilde{V}$ & $\theta_u' \neq \theta_u$:

- Compute θ_u from equation 11.
- Update θ, $n(\theta)$ and $f(\theta)$ grids and interpolate/extrapolate $\widetilde{V}$ to make it consistent with the updated grids. Denote the updated functions by $'$.
- Solve for $\widetilde{V}(\theta_j, \theta_i)$ for all $i \geq j$, as a function of $\widetilde{V}', \theta', n', f'$ from equation 10.
- Compute error and update: $\widetilde{V} = \widetilde{V}'$ and $\theta = \theta'$.

A.3 Wage Function

In this section I denote $W(\theta_i, \theta_j) \equiv W_{ij}$, $\omega(\theta_i, \theta_j) \equiv \omega_{ij}$, $\widetilde{V}(\theta_j, \theta_i) \equiv V_{ji}$, $V(\theta_i) \equiv V_i$, and $f(\theta_i) \equiv f_i$.

Start with the worker value function and plugging in the Nash Bargaining equation:

$$
\begin{aligned}
(\gamma + \delta) W_{ij} = \omega_{ij} + \delta V_u + \lambda_1 \Bigg[\sum_{x=i+1}^{N} \Big((1-\alpha) V_{ix} + \alpha V_x - W_{ij} \Big) n_x f_x \\
+ \sum_{x=j+1}^{i-1} \Big((1-\alpha) V_{xi} + \alpha V_i - W_{ij} \Big) n_x f_x + \Big(V_i - W_{ij} \Big) (n_i - 1) f_i \Bigg]
\end{aligned}
$$

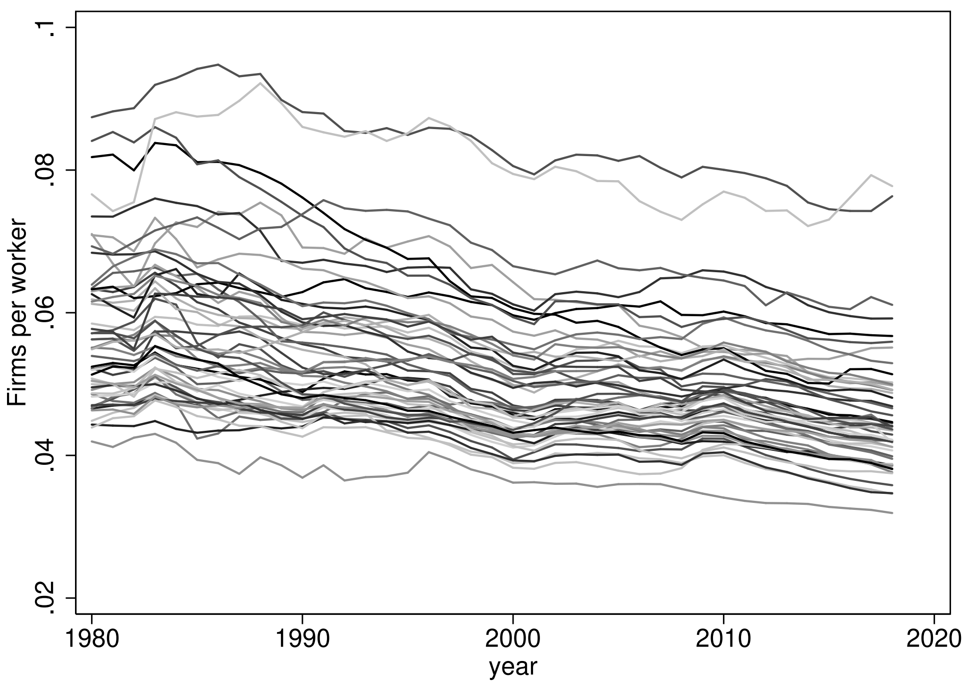
Then the wage function can be expressed as:

$$
\begin{aligned}
\omega_{ij} = & \Bigg(\gamma + \delta + \lambda_1 \Bigg[\sum_{x=i+1}^{N} n_x f_x + \sum_{x=j+1}^{i-1} n_x f_x + (n_i - 1) f_i \Bigg] \Bigg) \cdot \Big((1-\alpha) V_{ji} + \alpha V_i \Big) \\
& - \delta V_u - \lambda_1 \Bigg[\sum_{x=i+1}^{N} \Big((1-\alpha) V_{ix} + \alpha V_x \Big) n_x f_x + \sum_{x=j+1}^{i-1} \Big((1-\alpha) V_{xi} + \alpha V_i \Big) n_x f_x + V_i (n_i - 1) f_i \Bigg]
\end{aligned}
$$

Thus, the wage function, ω_{ij}, $i \in \{\theta_u, \cdots, \theta_N\}, j \leq i$, can be expressed as a function of equilibrium outcomes $\widetilde{V}$ and θ_u.

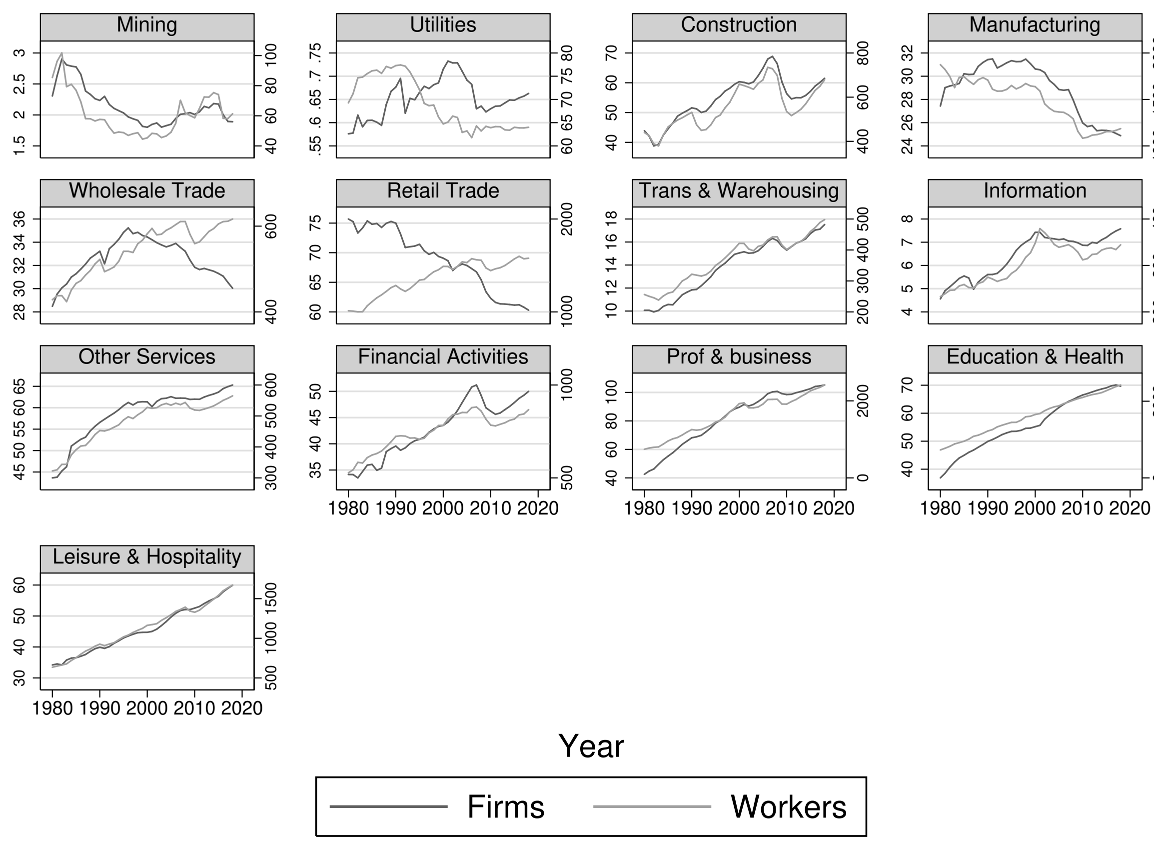
B Appendix Tables & Figures

Figure A1: Firms per Worker, state-wise, 1979-2018



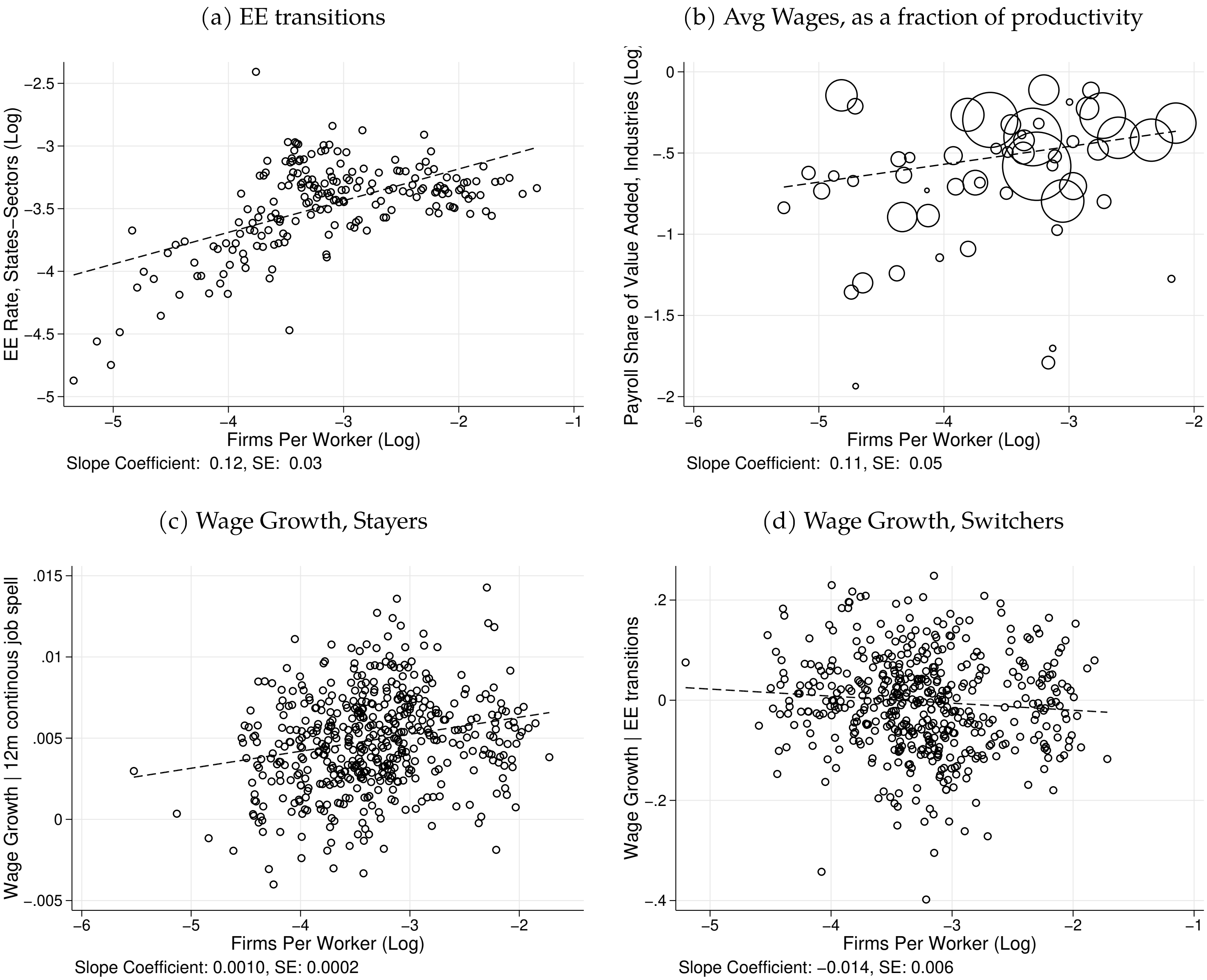
Notes: This figure shows the ratio of the number of firms to the number of workers for each state the US economy, over 1979-2018 using the Business Dynamics Statistics.

Figure A2: Number of Firms and Workers (in tens of thousands), 1979-2018



Notes: This figure plots the number of firms (left y-axis, in tens of thousands) and the number of workers (right y-axis, in tens of thousands) for each two digit NAICS sector of the US economy, over 1979-2018 using the Business Dynamics Statistics.

Figure A3: Cross-sectional Correlations in the Data



Notes: This figure plots the model-relevant outcome variables and firms per worker. Panel (a) plots the 2012-17 average of the firms per worker from the BDS and EE rates from the LEHD data across state × two-digit NAICS sector pairs. Panel (b) plots the 2012-17 average of the firms per worker and the payroll share of gross value added from the BLS across disaggregated industries. Each cell is weighted by its employment share. All variables are expressed in logs. Panel (c) and (d) present binned scatter plots of individual wage growth over a 12-month job spell and monthly wage growth associated with EE transitions from the SIPP against the firms per worker faced by the individual in their state and sector between 1996-2000.

Table A1: First Stage Estimates of Number of Firms per Worker

(a) First Stage Regressions for Log (Wages of J2J Hires) on Log(Firms per Worker)

	(1)	(2)	(3)
Avg Log Firms Per Workers in other MSAs	0.864***	0.710***	0.718***
	(0.0300)	(0.0267)	(0.0266)
Firm controls		✓	✓
MSA-Year FE			✓
Observations	91944	67448	67431
R^2	0.940	0.968	0.972
F	829.3	192.1	182.1

(b) First Stage Regressions for Log (Wages of NE Hires) on Log(Firms per Worker)

	(1)	(2)	(3)
Avg Log Firms Per Workers in other MSAs	0.868***	0.702***	0.711***
	(0.0299)	(0.0262)	(0.0263)
Firm controls		✓	✓
MSA-Year FE			✓
Observations	92625	66907	66891
R^2	0.936	0.968	0.972
F	844.9	195.0	182.5

(c) First Stage Regressions for Log (Wages of EN Separations) on Log(Firms per Worker)

	(1)	(2)	(3)
Avg Log Firms Per Workers in other MSAs	0.849***	0.688***	0.697***
	(0.0305)	(0.0267)	(0.0266)
Firm controls		✓	✓
MSA-Year FE			✓
Observations	93488	66836	66819
R^2	0.933	0.968	0.972
F	772.3	193.5	180.7

Notes: This table displays estimates of the first stage OLS regression of log of number of firms per worker on the average of log firms per worker in a sector-MSA-year cell across all other MSAs in that sector and year. All specifications control for year and market (sector x MSA) fixed effects. Sub-tables (A1a)-(A1c) respectively correspond to the second stage regression where the dependent variable is log of wages associated with job to job hires, nonemployment-to-employment hires, and employment-to-nonemployment separations. Sectors are defined as two-digit NAICS industries. Firm controls include the fraction of workforce in each cell belonging to different firm age, and firm size groups. SEs clustered at MSA x Sector level. Sample trimmed at 5 and 95 percentiles. Source: BDS, QWI and Job-to-Job (J2J) data by the LEHD. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2: OLS Regressions of Labor Market Transitions on Number of Firms and Number of Workers

	Log EE Transitions		
	(1)	(2)	(3)
Log Firms	0.568***	0.566***	0.569***
	(0.0165)	(0.0173)	(0.0177)
Log Workers	0.378***	0.374***	0.367***
	(0.0141)	(0.0146)	(0.0148)
MSA-Year FE		✓	✓
Sector-Year FE			✓
Observations	69793	69726	69726
R^2	0.957	0.961	0.963

Notes: This table displays regressions of EE transitions on the number of firms and number of workers. The dependent variable is log of Employer-to-Employers Separation Counts. All regressions control for MSA, year, and sector FEs as well as the full set of controls, including the fraction of workforce in each sector-MSA-year cell belonging to different age, education, firm age, and firm size groups. Column (2) further includes MSA x year fixed effects, and column (3) additionally includes Sector x year fixed effects. Sectors are defined as two-digit NAICS industries. SEs clustered at MSA x Sector level in parenthesis. Sample trimmed at 5 and 95 percentiles. Source: BDS, QWI and Job-to-Job (J2J) flows data by the LEHD, 2000-2017. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$