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

Sadhika Bagga†

September 12, 2022
(Link to latest version)

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 employer firms per employed worker, drives the decline in worker mobility and wages. The model has two main ingredients: (i) there exists a finite number of employers that differ in productivity, and (ii) employers exert market power by excluding their offers from the set of outside options faced by their employees. The combined effect of both 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 model accounts for 2/3rd of the decline in employer-to-employer transitions rate and ten percent 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

*I am grateful to Olivier Coibion, Andreas Mueller, and Aysegul Sahin for their guidance and support. I thank Alex Bick, Serdar Birinci, Andres Drenik, Rosemary Kaiser, Fatih Karahan, Pawel Krolikowski, Marianna Kudlyak, Ioana Marinescu, Anushka Mitra, Nicolas Petrosky-Nadeau, Laura Pilossoph, Anna Stansbury, Giorgio Topa, Choongryul Yang, and conference and seminar participants at UT Austin, NBER Wage Dynamics of the 21st Century Spring 2021, SOLE 2022, ASSA 2022, St. Louis Fed, SF Fed, NY Fed and Oxford NuCamp PhD Workshop 2021 for helpful comments and suggestions. I thank Pawel Krolikowski for sharing his code with me. I acknowledge the Texas Advanced Computing Center at UT Austin for providing HPC resources that have contributed to the calibration results reported within this paper. All errors are my own.

†The University of Texas at Austin. Email: sbagga@utexas.edu

1 Introduction

A recent and burgeoning body of empirical literature has 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] This paper examines the link between employer market power and wages by exploring another macroeconomic aggregate that has seen a decline 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, primarily introduced by assuming the finiteness of firms 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 in the relevant labor markets of workers is associated with a slowing of wages and a decline in job-to-job flows.

The theoretical predictions of the model can be seen in the 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 potentially imply restricting 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 wages in equilibrium, explain the aggregate decline in the two outcomes resulting from decreasing competition among firms for workers?

[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).

This paper attempts to 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 discounts the outside option of the worker, consequently putting downward pressure on the negotiated wage and gives 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 transitions from job-to-job and 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 worker's 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. Next, I decompose these equilibrium links into two main channels: One, the mega-firm channel, where a decrease in the number of firms leads to 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. Two, the retaliation channel, which precludes the 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. Next, 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 10 percent of the decrease in wages as a fraction of productivity between the 1980s and 2010s.

To evaluate the model's predictions from an empirical standpoint, I examine the behavior of the model-relevant measure of labor market competition in the data. Specifically, I document trends in the number of firms relative to the number of workers in the US economy over the last four decades. Measuring 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. 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.

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. One, 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. Two, I document a positive relationship between the number of firms per worker and the payroll share of value-added, which proxies wages/productivity across disaggregated industries. Three, 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. Four, in the spirit of recent literature 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 the average wages. Overall, the empirical evidence on EE transitions rate, wage growth, and average wage levels is consistent with the model's predictions.

This paper's theoretical and empirical findings contribute to various strands of 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. One, 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. Two, Schubert, Stansbury & Taska (2022) present 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: One, 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 to falling EE transitions rate, apart from falling wages.[4]

Other theoretical models studying imperfect competition in the labor market and its

[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 build a search model with finite firms and endogenous vacancy posting and find a negative correlation between HHIs and job flows and wages, in line with the results presented in this paper.

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 larger markdowns relative to 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 reallocation of value-added towards 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 averages 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. One, 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. Two, Schubert, Stansbury & Taska (2022) compute a measure of outside option 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 model proposed. I 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 and their implications on the outcomes. Section 3 describes the calibration methodology, examines the model fit. It further provides details of the qualitative and quantitative implications of the model, and explains the mechanism in effect. Section 4 presents an empirical examination of key predictions of the model on wages and job transitions. Section 5 concludes.

2 Model

2.1 Agents

Let the continuous-time economy be 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]

Let there be 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 $n_i \cdot f(\theta_i)$.[6] On matching, firms

[5]The exposition of the model is inspired by Jarosch (2021).
[6]With the normalization that $\sum_{i=1}^{N} n_i f(\theta_i) = 1$

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 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 $V(\theta_i) = W(\theta_i, \theta_j) + J(\theta_i, \theta_j)$.[7] 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

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

firm, and joining the more-productive poaching firm:[8]

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

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 renegotiation 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, making the poaching firm's offer incredible. 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 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

[8] 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.

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.[9] 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 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

[9] 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 of 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.

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 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.[10] 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

[10] 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.

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.[11]

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

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

The flow payoff to the firm from a match is equal to the output, $y(\theta_i)$, less the wages 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 that 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.[12]

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

[11] 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.

[12] 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 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:

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

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

The left-hand side of 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 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 that 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 of solving the model numerically is detailed in Appendix A.2. Finally, the equilibrium wage function is derived in Appendix A.3.

3 Calibration

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 varying market power of firms and workers and evaluate the model's qualitative and quantitative predictions.

3.1 Methodology

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.[13] 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 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.[14] I arrive at a monthly UE and EU transitions probability averaging 44.9 percent and 3.78 percent, respectively.

[13] 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 do not differ if the model targets 2012-17 and is evaluated against 1985-90.

[14] The 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.

The monthly EE transitions 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 transitions 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.

Next, I set the total number of firms in the model to 50 to match the employment-weighted median number of firms in a metropolitan area-sector pair in 1985-90 in the Business Dynamics Statistics (BDS). 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).[15]

I set the five-dimensional vector $n(\theta)$ to match the distribution of firms over the job ladder. As wage ladders strongly proxy job ladders (Haltiwanger, Hyatt, Kahn & McEntarfer 2018), $n(\theta)$ is set to match the share of firms over the offered wage distribution. I utilize data from Burning Glass Technologies that contain information on the near-universe of job vacancies posted online. These data document employer names and the minimum and maximum salaries associated with the vacancy posting. I first compute the average wage over all vacancies posted by a single employer. Based on this, I then rank employers and compute their share over five equally sized bins of the average offered wage distribution.[16] I arrive at the following distribution of the share of firms over the wage quintiles: {0.24,0.34,0.24,0.12,0.06}.[17] This is interpreted as: 24 percent of the sample of employers are in the lowest offered wage tier of the job ladder whereas six percent lie on the right tail.[18]

[15] I set the number of employer-firm productivity levels to be five. This does not include θ_u, which is always assumed to be a productivity level with a single non-employer firm.

[16] I assume employer productivity and wages associated with their vacancies are positively correlated, and a more productive employer offers higher wages across all their vacancies.

[17] This distribution looks similar if computed for the aggregate US economy or average local labor market defined as a state and NAICS-2 digit sector.

[18] An alternative way to calibrate the number of firms in the worker's labor market would be to target the average number of applications filed by job seekers. Faberman & Kudlyak (2019) find that the average job-seeker filed 7.1 applications per month and Marinescu & Rathelot (2018) document that the average unemployed job seeker filed around 12.8 applications in a month. Since the model includes job search by the unemployed and employed, I also calibrated the model by setting the number of firms to 10, uniformly distributing them over the productivity grid, and found qualitatively similar results.

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 about 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 gets 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.

Finally, the discount rate, γ, is set to match an annual interest rate of four percent. The flow payoff of leisure, z, is normalized to zero, and output across all matches, $y(\theta_i)$, is expressed as θ_i additively scaled up by a constant output shifter, ζ. This is done so that: one, the unknown reservation productivity remains below the first point of the productivity grid (zero), and two, the least productive firm produces produces non-zero output. The output shifter is chosen such that the reservation productivity level, net of the output shifter, targets 60 percent of the Average Labor Productivity (ALP) in the economy. This value is within the 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, net reservation wage as a fraction of average labor productivity, and wage growth associated with continuous job spells) to inform seven parameters $(\lambda_0, \lambda_1, \delta, \nu, \mu, \zeta, \alpha)$.

Table (1) shows the model's calibrated parameters that minimize the distance between

Table 1: Parameter Values

	Parameter	Value	Target/Source
		Externally Calibrated	
N	# Productivity Levels	5	Bayer & Kuhn (2018)
$\sum_{i=1}^{N} n_i$	# Firms	50	MSA x Sector (BDS)
$\{n_i / \sum_{i=1}^{N} n_i\}_i$	Firm Share|Job Ladder	{0.24, 0.34, 0.24, 0.12, 0.06}	Firm Share|Wage Distn. (BGT)
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	0.10	E [EE]
δ	Separations Rate	0.037	E [EU]
ν, μ	Job Offer Distn $\sim$ Beta	1.07, 0.77	SD (Wages); wΔ|Job Spell
α	Worker's Bargaining Share	0.42	Mm Ratio
ζ	Output Shifter	1.8	Net Reservation Wage/ALP

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 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 12-month continuous job spells. Net reservation wage/ALP stands for the reservation productivity level, net of the output shifter, as a fraction of the average labor productivity of the economy. BDS stands for Business Dynamics Statistics, and BGT stands for Burning Glass Technologies.

Table 2: Model-generated Moments and their Targeted Values

Moment	Model	Data	Data Source
E [UE], %	46.6	44.9	CPS, 1985-90
E [EE], %	2.82	2.83	CPS, 1985-90
E [EU], %	3.71	3.79	CPS, 1985-90
SD (Wages)	0.21	0.24	Hall & Mueller (2018)
Mm Ratio	1.41	1.50	Hornstein, Krusell & Violante (2011)
E [Wage Growth, 12m Job Spell], %	0.50	0.90	SIPP, 1996-00
Net Reservation Wage/ALP	0.61	0.60	Mas & Pallais (2019)

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 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. Net reservation wage/ALP stands for the reservation productivity level, net of the output shifter, as a fraction of the average labor productivity of the economy.

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.

The following section presents two counterfactual exercises. First, I vary the market power of employers by changing the number of firms in the model. In the second, I vary the bargaining power of workers in the wage negotiation protocol. In each case, I discuss the response of model moments related to wages and worker transitions and the equilibrium behavior of the model's functions.

3.2 Equilibrium Effects of Declining Number of Firms

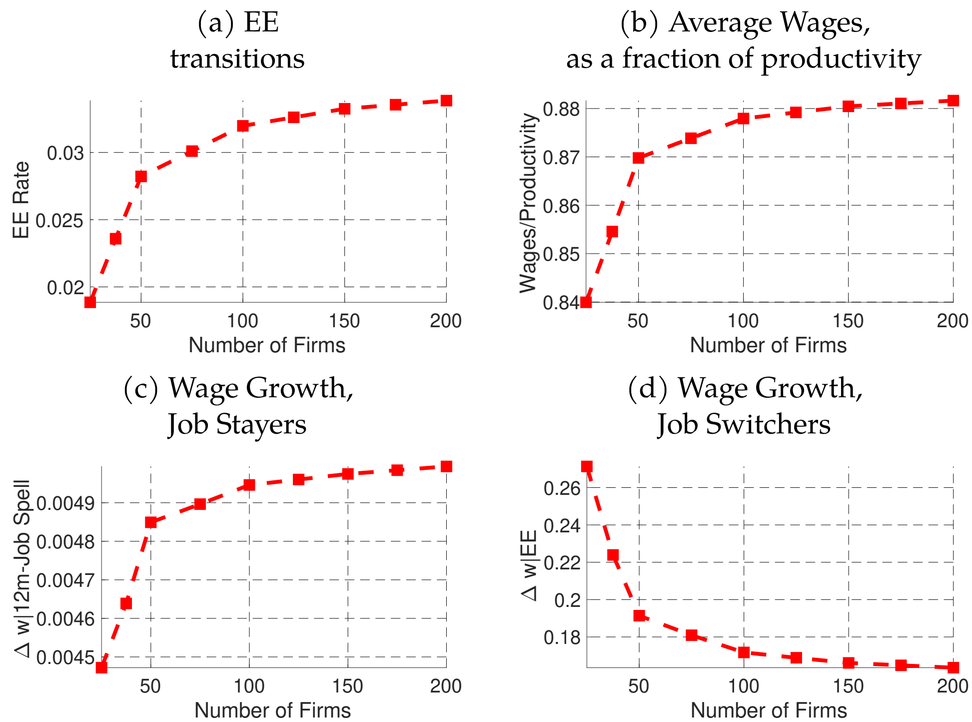
This section analyzes the model's implications when the number of firms varies from its baseline level. In particular, I hold the productivity of each firm at a fixed level and all parameters of the model at their calibrated values and only vary the number of firms, n_i, within each productivity level.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

3.2.1 Qualitative Implications

Figure (1) 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 distribution of firms over the job ladder, constant. Panel (1a) 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 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, 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 (1b) shows that wages/productivity are also increasing in the number of firms. This happens for two reasons: One, 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. Two, the strong non-linearity in the plot is due to firms imposing

Figure 1: 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.

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 worker 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 more considerable decrease in wages.

The growth rate of wages associated with job switches and within-job wage transitions are shown in panels (1c) and (1d). 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 increasingly get a within-job wage increase as employer competition increases, resulting in the rising wage growth of job stayers. At the same time, 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.

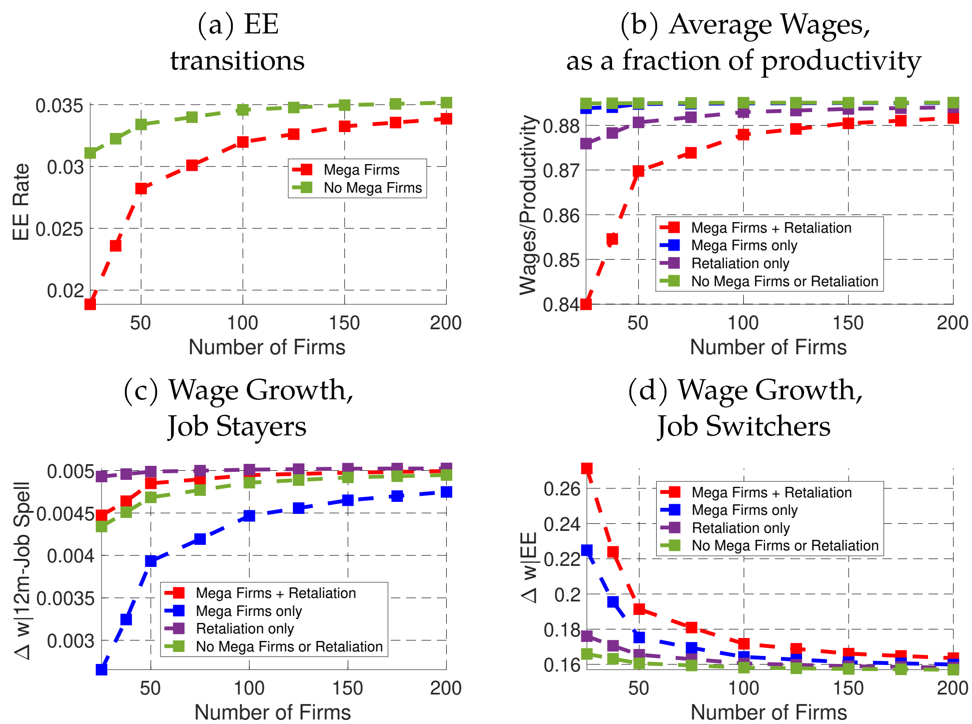
In terms of equilibrium response of the model's functions, as competition in the economy intensifies, the value to the employed and unemployed worker increases while that to the firm reduces. This happens because as firms become increasingly atomistic, their ability to discount workers' outside options 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. Appendix A.4 shows the qualitative implications of the model when the bargaining power of workers is changed.

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 large. As employment becomes concentrated in large firms, workers in these firms face a reduced probability of job finding. This reduces the worker's value for 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 Chan-*

Figure 2: 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.

nels: This is the benchmark version of the model shown in red in Figures 1 and 2. (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 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., {0.24, 0.34, 0.24, 0.12, 0.06}, 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 (2) 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 (1).

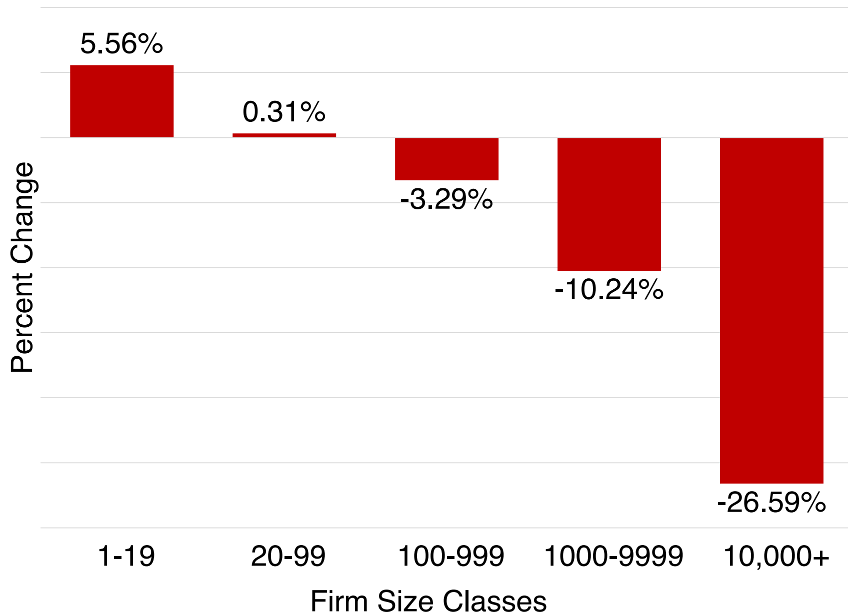
Panel (2a) shows that the EE transitions rate is increasing in the number of firms across the two versions of the model, with and without mega-firms. Compared to a model with uniformly distributed firms (green line), in a model with mega-firms (red line), firms at the top of the job ladder are fewer 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 (2b) shows that across all versions of the model, wages/productivity are increasing 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 retaliation channel alone (purple line). The absence of the retaliation channel (blue and green lines) leads to a nearly flat wage response.

Panels (2c) and (2d) 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 (2c) and (2d). As wage levels are suppressed relative to productivity in the presence of retaliation (Panel 2b), 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 (2c) and (2d).

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 Figures (1c) and (1d), where in an environment of low competition due to fewer number of firms, wage growth of job switchers high, and that of job stayers was low. 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

Figure 3: Firms per Worker over Firm Size Bins, Changes in 2012-17 relative to 1985-90



Notes: This figure shows the changes from 1985-90 to 2012-17 in the long-run average of the ratio of the number of firms to workers over firm size classes, using the Business Dynamics Statistics.

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).

3.2.3 Quantitative Implications

Next, I quantify the model's implications when the number of firms, holding constant all other model parameters, varies by the extent it has changed in the data between 1985-2017. Specifically, I undertake two experiments: (1) I simulate a 13.1% decrease from the 1980s to 2010s in the number of firms at each productivity level. (2) I simulate a non-uniform change in the number of firms over the job ladder. I describe each of these in detail below.

Table (3), panel (a) compares the average EE transitions rate and the real hourly compensation/real hourly output (wages/productivity) for the US economy in 1985-90 and 2012-17. For both the periods, the long-run averages of the two moments have been computed from the CPS and BLS, respectively.[19] Data from the Business Dynamics Statistics

[19] I use the EE transitions probability series supplied 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)

	(a) Data			(b) Model: Uniform Δ		(c) Model: Nonuniform Δ	
Moment	1980s	2010s	% Change	% Change	% Explained	% Change	% Explained
Firms Per Worker	0.049	0.042	-13.1				
E[EE], %	2.83	2.29	-18.9	-8.7	46.0	-13.1	69.3
w/p, normalized index	1.00	0.90	-9.7	-0.89	9.1	-1.1	11.3

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 long-run average of the moment from 1985-90 to 2012-17. Panel (a) shows (i) five-year annual averages of the number of firms per employee from the BDS, (ii) average employment-to-employment flows measured at a monthly frequency and averaged over a five-year horizon from the CPS, and (iii) 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) simulates a 13.1% change in firms per worker in the model and computes the corresponding changes in the moments. Panel (c) simulates changes in firms per worker in each productivity bin corresponding to Figure (3) and reports the changes in the model moments.

is used to compute firms per worker for the 1980s and 2010s.

The US economy observed a 13.1 percent decline in the number of firms per worker between the 1980s and the 2010s. To facilitate a comparison between the two periods in the model, I first decrease the number of firms by the same fraction at each productivity level, holding the number of workers fixed. This results in a decline in EE transitions of 8.7 percent, accounting for about a fourth of the overall decrease over the two periods, as shown in Panel (b) of table (3). Wages/productivity declines by 0.9 percent, accounting for about nine percent of the overall decrease in the data.

In the next experiment, I explore the evolution in firms per worker over the firm size ladder.[20] Figure 3 plots changes in firms per worker between the 1980s and 2010s for five

[20] I use firm size ladder to proxy for the job ladder because of the lack of data on firm wage ladder dating back to the 1980s. Whether and how firm size is linked to the job ladder is a debated topic in the literature on firm ladders. On the one hand, the classic models such as those of Burdett & Mortensen (1998) postulate a positive relationship between firm size and wage ladder; more recent work by Haltiwanger, Hyatt, Kahn & McEntarfer (2018) explores poaching patterns by firm size showing less evidence of a size ladder. They argue that firm age drives the wedge between the size ladder and productivity: some young firms are smaller but highly productive and fast-growing. They, therefore, poach workers, on the net, from all along the firm size ladder. Controlling for firm age, they find evidence supporting a firm size ladder. The BDS data also contain firm and employment counts by firm age and firm size cells. However, the data on firm age are prone to being left-censored, and many firm age x size cells have missing values due to Census disclosure norms. To find evidence of firms per worker over the firm size ladder, after controlling for firm age, I first use data on firm age and drop all observations before 1988 so that none of the firm age categories are left censored. This leaves me with two age categories: firms aged 1-10 years and those aged 11+ years. To tackle the problem of missing observations, I aggregate the three largest firm size classes. This leaves me with the following 8 firm size bins: 1-4, 5-9, 10-19, 20-99, 100-499, 500-999, 1000-2499 and 2500+ employees. I finally fill in the missing firm age x firm size cells by imputing their differences from the data on aggregate firm

firm size bins from the BDS, where firm size is measured by the size of the workforce. 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 overtime.[21]

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. Specifically, proxying the rungs of the job ladder by the firm size bins, I vary the number of firms at each productivity level by the extent to which it has changed in the corresponding size class in Figure 3. This translates to a decline in firms at the upper rungs of the job ladder and an increase in the lower ones. Table (3), panel (c) shows that simulating such a disproportionate change in the number of firms in the model, further exacerbates the decline in the two moments. The model now explains two-thirds of the overall decline in EE transitions and a tenth of the decrease in wages relative to productivity.

This section showed the qualitative and quantitative predictions of the model when the number of firms is varied, 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 1/4th - 2/3rd of the decline in EE transitions, and 9-11 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. One, more chances for workers to quit their firms, resulting in a high rate of job-to-job transitions. Two, 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.

age and aggregate firm size provided by the BDS. I find that the distribution of firms per worker by firm size classes, for the older firm-age group, saw similar long-run trends as the ones observed in Figure 3.

[21] See section 4.2 for a discussion on this.

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.[22][23] 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.[24] I document evidence of a persistent and long-run decline in the number of firms per worker in the US, starting from the early 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 the Business Dynamics Statistics (BDS). The BDS is part of the Longitudinal Business Database (LBD) of the US Census Bureau. It covers approximately

[22]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.

[23]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.

[24]The number of firms per worker is indicative of the competition for employed workers. Assuming all firms are hiring and controlling for the average firm size and worker characteristics, the higher the ratio, the more intense the competition among firms for workers. For a given number of workers, the number of firms correlates positively with the employment-based HHI. Further, from the 1990s, the firms per worker evolved in line with employment concentration measures of Autor et al. (2020) for several super sectors of the economy. Without including unemployed workers or nonparticipants, the firm-to-worker ratio acts as a lower bound on the degree of competition faced by employed workers and an upper bound on the degree of competition faced by firms.

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 regions and industries. Still, unlike the BDS, all states did not enter the LEHD program simultaneously, with the earliest states' data available starting from 2000.

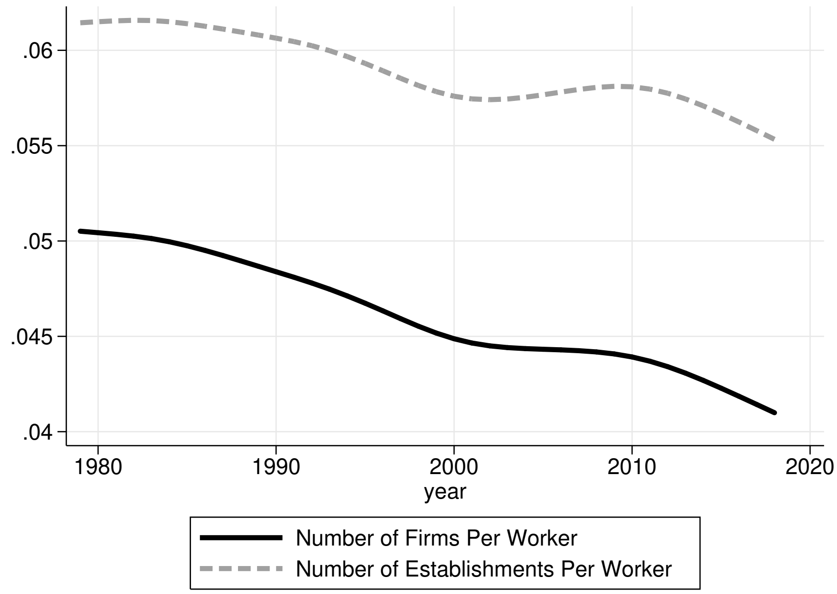
To combine data from the BDS and LEHD with measures of worker and firm demographics, I use local labor market statistics from the Quarterly Workforce Indicators (QWI). The QWI is also sourced from the LEHD program, and the earliest states entered the sample in 1990. QWI provides data on the composition 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.[25] The dataset

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

Figure 4: 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.

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 (4) plots trends in firms- and establishments- per worker from 1979-2018. Two observations are immediately apparent. One, both ratios experienced a long-run decline over the sample period, with firms per worker recording a steeper decline

(18.3%) 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.[26] Two, 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, I examine changes in firms per worker within sectors, regions, and sector-by-region cells.

Table (4) reports long-run averages of firms per workers within sectors, or two-digit NAICS industries, over five-year horizons. A few observations are noteworthy. One, 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 (A3) 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. Two, service sectors such 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 to workers. 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 that did not experience much change. I conclude that the aggregate decline in Figure (4) was not a result of compositional changes across sectors over the same period. In fact, Table (4) shows the opposite:

[26] 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 largest 20 firms in an industry (Autor, Dorn, Katz, Patterson & Van Reenen 2020) and wage markdowns (Yeh, Macaluso & Hershbein 2022).

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.

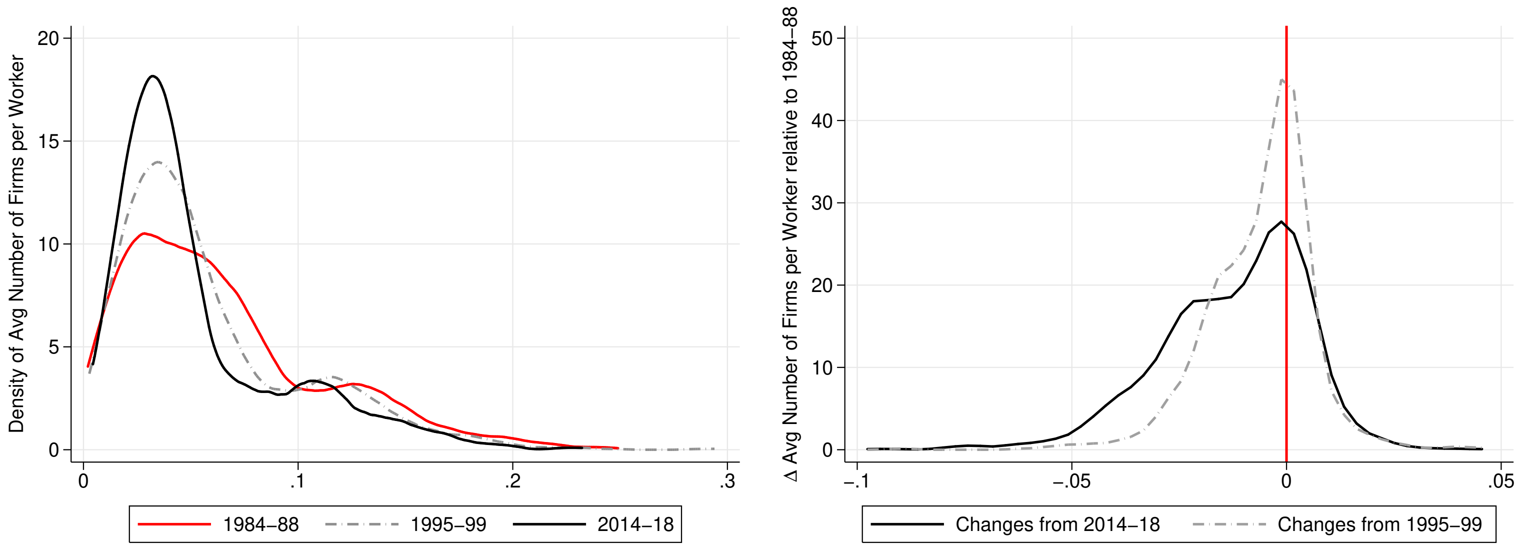
sectors with the highest firms per worker in the 1980s US economy have expanded, while those with lowest firms per worker have contracted.[27] The aggregate decline in firms per worker was also not a result of shifting employment composition across different regions. Figure (A2) in the Appendix plots 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 (5) 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.

To sum, the decline in the number of firms per worker is evident in the aggregate econ-

[27] It is also noteworthy that the firm to worker ratio evolved in line with employment concentration measures of Autor et al. (2020) from the 1990s for several super-sectors of the economy.

Figure 5: 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.

omy, as well as within sectors, states, and a majority of sector-by-state cells. In the next section, I show that this decline is correlated to the pace of job mobility, average wages and wage growth of job stayers and movers, in line with the predictions of the model.

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 (A4) shows that scatter plots of raw data summarizing these relationships are consistent with the model's predictions. Panel A4a 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 firms per worker also had a higher EE transitions rate. Panel A4b 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 A4c and A4d 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.

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:

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

where $log(\textit{EE Rate})_{jmt}$ is the log of average job-to-job transition rates in sector j, MSA m, and in year t. The main explanatory variable $log(\textit{Firms Per Worker})$ 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 metropolitan area-sector pairs, controlling for time-varying characteristics of sectors and metropolitan areas.[28] 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 transition 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

[28] 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 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 number of firms per worker in each column. The dependent variables are logs of 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

increase of about 0.084 log points in the EE transition 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 transition 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 positive and significant, with log firms being of a higher magnitude.[29]

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 predictions about declining labor market dynamism in the face of the declining number of firms per worker.

[29] 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.

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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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 compensation 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:

$$log(Wages/Productivity)_{jt} = \beta \cdot log(Firms\ Per\ Worker)_{jt} + \alpha_j + \alpha_t + \epsilon_{jt} \tag{13}$$

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

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 log of 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 log of 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). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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.[30] 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 neglible increase in 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 one 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:

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

[30] 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.

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.[31] 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 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.[32] This instrument captures the variation in firms per worker that is not driven by changes in a sector of any particular 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 for. 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 workers. 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.[33]

[31] 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 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.

[32] 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.

[33] A key outcome of the model by Burdett & Mortensen (1998) is that larger firms pay higher wages. This

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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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 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.

5 Conclusions

I present a tractable model of the labor market with finite firms that are heterogeneous in productivity, and random search, both off and on the job. Wage negotiations follow a sequential auctions protocol, and worker's value from a match is determined by their employer's productivity and outside options. Firms exercise market power in the wage bargain by removing their offers from their employees' outside options. The model is calibrated to fit long-run moments of the US economy and can reproduce empirically observed labor market flows and wage dispersion.

Next, I evaluate the predictions of the model by varying the market power of firms. First, I vary the number of firms in the market, where a higher number of firms corresponds to increased firm competition for workers and diminishing firm market power. I document that job-to-job flows, average wages (normalized by productivity), and worker's values derived in the model increase with the level of firm competition in the economy. Further, as more firms crowd the market, wage growth of job stayers increases while that of job switchers decreases. Second, I highlight the main

is documented robustly in the empirical literature, pioneered by Brown & Medoff (1989), and more recently in Bloom, Guvenen, Smith, Song & von Wachter (2018).

channels at play in the model. Finally, I assess the quantitative implications of the model by decreasing the number of firms per worker in the model to the same extent that it decreased in the data between the 1980s and 2010s. I find that the model can predict about 2/3rd of the overall decline in EE rate and 10 percent of the decline in wages relative to productivity.

I explore these predictions of the model empirically, by examining the behavior of the number of firms per worker in the US economy over time. I find that the ratio has been trending downwards, especially from the late 1990s, and that the decline is pervasive within states, sectors, and states-by-sectors. Finally, I evaluate the model's implications in the cross-section and find empirical elasticities that are consistent with the predictions of the model.

To close by noting that, by examining the average behavior of firms to worker ratio, job transitions, and wages in sub-markets, this paper is able to offer an overview of how the model-relevant measure of labor market competition has evolved, and how it is related to the outcomes of the model. 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 labor market dynamism is possible. The analysis presented in this paper also 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.

References

Autor, D., Dorn, D., Katz, L. F., Patterson, C. & Van Reenen, J. (2020), 'The fall of the labor share and the rise of superstar firms', *The Quarterly Journal of Economics* **135**(2), 645–709.

Azar, J., Marinescu, I. & Steinbaum, M. (2020), 'Labor market concentration', *Journal of Human Resources* pp. 1218–9914R1.

Azar, J., Marinescu, I., Steinbaum, M. & Taska, B. (2020), 'Concentration in us labor markets: Evidence from online vacancy data', *Labour Economics* **66**, 101886.

Azkarate-Askasua, M. & Zerecero, M. (2020), 'The aggregate effects of labor market concentration', *Unpublished Working Paper* .

Bayer, C. & Kuhn, M. (2018), 'Which ladder to climb? wages of workers by job, plant, and education'.

Benmelech, E., Bergman, N. K. & Kim, H. (2020), 'Strong employers and weak employees: How does employer concentration affect wages?', *Journal of Human Resources* pp. 0119–10007R1.

Berger, D., Herkenhoff, K., Kostol, A. R. & Mongey, S. (2022), 'Dynamic oligopsony and inequality', *Manuscript* .

Berger, D., Herkenhoff, K. & Mongey, S. (2022), 'Labor market power', *American Economic Review* **112**(4), 1147–93.

Blanchard, O. J., Diamond, P., Hall, R. E. & Murphy, K. (1990), 'The cyclical behavior of the gross flows of us workers', *Brookings papers on economic activity* **1990**(2), 85–155.

Bloom, N., Guvenen, F., Smith, B. S., Song, J. & von Wachter, T. (2018), The disappearing large-firm wage premium, *in* 'AEA Papers and Proceedings', Vol. 108, pp. 317–22.

Brown, C. & Medoff, J. (1989), 'The employer size-wage effect', *Journal of political Economy* **97**(5), 1027–1059.

Burdett, K. & Mortensen, D. T. (1998), 'Wage differentials, employer size, and unemployment', *International Economic Review* pp. 257–273.

Cahuc, P., Postel-Vinay, F. & Robin, J.-M. (2006), 'Wage bargaining with on-the-job search: Theory and evidence', *Econometrica* **74**(2), 323–364.

Caldwell, S. & Danieli, O. (2022), 'Outside options in the labor market'.

Caliendo, L., Monte, F. & Rossi-Hansberg, E. (2015), 'The anatomy of french production hierarchies', *Journal of Political Economy* **123**(4), 809–852.

De Loecker, J., Eeckhout, J. & Unger, G. (2020), 'The rise of market power and the macroeconomic implications*', *The Quarterly Journal of Economics* **135**(2), 561–644.

Diamond, P. A. & Şahin, A. (2016), Disaggregating the matching function, Technical report, National Bureau of Economic Research.

Elsby, M. W., Hobijn, B. & Şahin, A. (2013), 'The decline of the us labor share', *Brookings Papers on Economic Activity* **2013**(2), 1–63.

Faberman, R. J. & Kudlyak, M. (2019), 'The intensity of job search and search duration', *American Economic Journal: Macroeconomics* **11**(3), 327–57.

Faberman, R. J., Mueller, A. I., Şahin, A. & Topa, G. (2022), 'Job search behavior among the employed and non-employed', *Econometrica* **90**(4), 1743–1779.

Forret, M. L. & Dougherty, T. W. (2004), 'Networking behaviors and career outcomes: differences for men and women?', *Journal of Organizational Behavior: The International Journal of Industrial, Occupational and Organizational Psychology and Behavior* **25**(3), 419–437.

Fujita, S. & Moscarini, G. (2017), 'Recall and unemployment', *American Economic Review* **107**(12), 3875–3916.

Fujita, S., Moscarini, G. & Postel-Vinay, F. (2022), Measuring employer-to-employer reallocation, Technical report, Mimeo.

Gouin-Bonenfant, E. (2022), Productivity dispersion, between-firm competition, and the labor share, *in* 'Society for Economic Dynamics. Meeting Papers', Vol. 1171.

Hagedorn, M. & Manovskii, I. (2008), 'The cyclical behavior of equilibrium unemployment and vacancies revisited', *American Economic Review* **98**(4), 1692–1706.

Hall, R. E. & Milgrom, P. R. (2008), 'The limited influence of unemployment on the wage bargain', *American economic review* **98**(4), 1653–74.

Hall, R. E. & Mueller, A. I. (2018), 'Wage dispersion and search behavior: The importance of non-wage job values', *Journal of Political Economy* **126**(4), 1594–1637.

Haltiwanger, J. C., Hyatt, H. R., Kahn, L. B. & McEntarfer, E. (2018), 'Cyclical job ladders by firm size and firm wage', *American Economic Journal: Macroeconomics* **10**(2), 52–85.

Hornstein, A., Krusell, P. & Violante, G. L. (2011), 'Frictional wage dispersion in search models: A quantitative assessment', *American Economic Review* **101**(7), 2873–98.

Hyatt, H. R. & Spletzer, J. R. (2016), 'The shifting job tenure distribution', *Labour Economics* **41**, 363–377.

Jarosch, G. (2021), Searching for job security and the consequences of job loss, Technical report, National Bureau of Economic Research.

Jarosch, G., Nimczik, J. S. & Sorkin, I. (2021), Granular search, market structure, and wages, Technical report, National Bureau of Economic Research.

Karahan, F., Michaels, R., Pugsley, B., Şahin, A. & Schuh, R. (2017), 'Do job-to-job transitions drive wage fluctuations over the business cycle?', *American Economic Review* **107**(5), 353–57.

Krueger, A. B. & Ashenfelter, O. (2018), Theory and evidence on employer collusion in the franchise sector, Technical report, National Bureau of Economic Research.

Manning, A. (2021), 'Monopsony in labor markets: a review', *ILR Review* **74**(1), 3–26.

Marinescu, I., Ouss, I. & Pape, L.-D. (2020), Wages, hires, and labor market concentration, Technical report, National Bureau of Economic Research.

Marinescu, I. & Rathelot, R. (2018), 'Mismatch unemployment and the geography of job search', *American Economic Journal: Macroeconomics* **10**(3), 42–70.

Mas, A. & Pallais, A. (2019), 'Labor supply and the value of non-work time: Experimental estimates from the field', *American Economic Review: Insights* **1**(1), 111–26.

Molloy, R., Trezzi, R., Smith, C. L. & Wozniak, A. (2016), 'Understanding declining fluidity in the us labor market', *Brookings Papers on Economic Activity* **2016**(1), 183–259.

Moscarini, G. & Postel-Vinay, F. (2012), 'The contribution of large and small employers to job creation in times of high and low unemployment', *American Economic Review* **102**(6), 2509–39.

Moscarini, G. & Postel-Vinay, F. (2017), 'The relative power of employment-to-employment reallocation and unemployment exits in predicting wage growth', *American Economic Review* **107**(5), 364–68.

Rinz, K. (2020), 'Labor market concentration, earnings, and inequality', *Journal of Human Resources* pp. 0219–10025R1.

Schubert, G., Stansbury, A. & Taska, B. (2022), 'Employer concentration and outside options'.

Shimer, R. (2005), 'The cyclical behavior of equilibrium unemployment and vacancies', *American economic review* **95**(1), 25–49.

Shimer, R. (2012), 'Reassessing the ins and outs of unemployment', *Review of Economic Dynamics* **15**(2), 127–148.

Starr, E., Bishara, N. & Prescott, J. (2020), 'Noncompete agreements in the us labor force', *Journal of Law and Economics* .

Yeh, C., Macaluso, C. & Hershbein, B. (2022), 'Monopsony in the us labor market', *American Economic Review* **112**(7), 2099–2138.
URL: *https://www.aeaweb.org/articles?id=10.1257/aer.20200025*

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:

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

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:

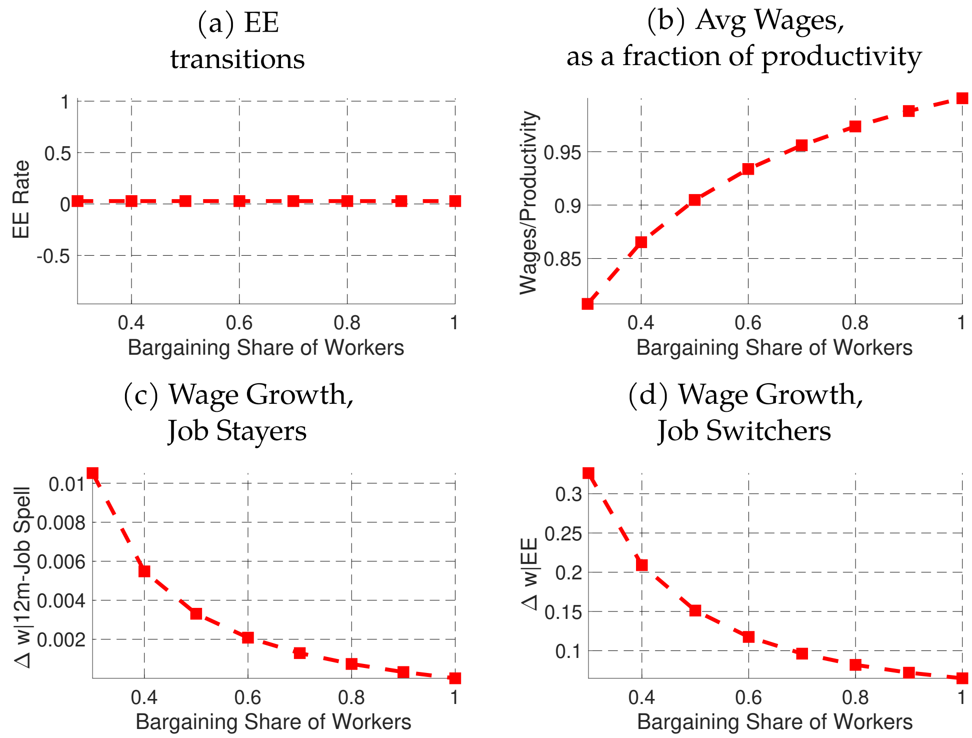
$$\begin{aligned}(\gamma+\delta)W_{ij} = \omega_{ij} + \delta V_u + \lambda_1 \Bigg[\sum_{x=i+1}^{N} \Big((1-\alpha)V_{ix} + \alpha V_x - W_{ij} \Big) n_x f_x \\ + \sum_{x=j+1}^{i-1} \Big((1-\alpha)V_{xi} + \alpha V_i - W_{ij} \Big) n_x f_x + \Big(V_i - W_{ij} \Big)(n_i - 1) f_i \Bigg]\end{aligned}$$

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.

Figure A1: The response of worker transitions and wages to changing bargaining power of workers



Notes: This figure displays the model-simulated moments in response to different values of α, holding all other parameters fixed at their calibrated values in Table (1).

A.4 Changing Bargaining Power of Workers and Firms

In this counterfactual exercise, I vary the market power of workers by changing the share of the joint match value accruing to them in a Nash bargain. The rising market power of workers corresponds to the falling market power of firms. Figure (A1) shows the response of the model moments with varying bargaining power of workers, α, holding all other parameters of the model as well as the number of firms in the economy constant. Figure (A1a) shows a constant response of EE transitions in response to varying α.

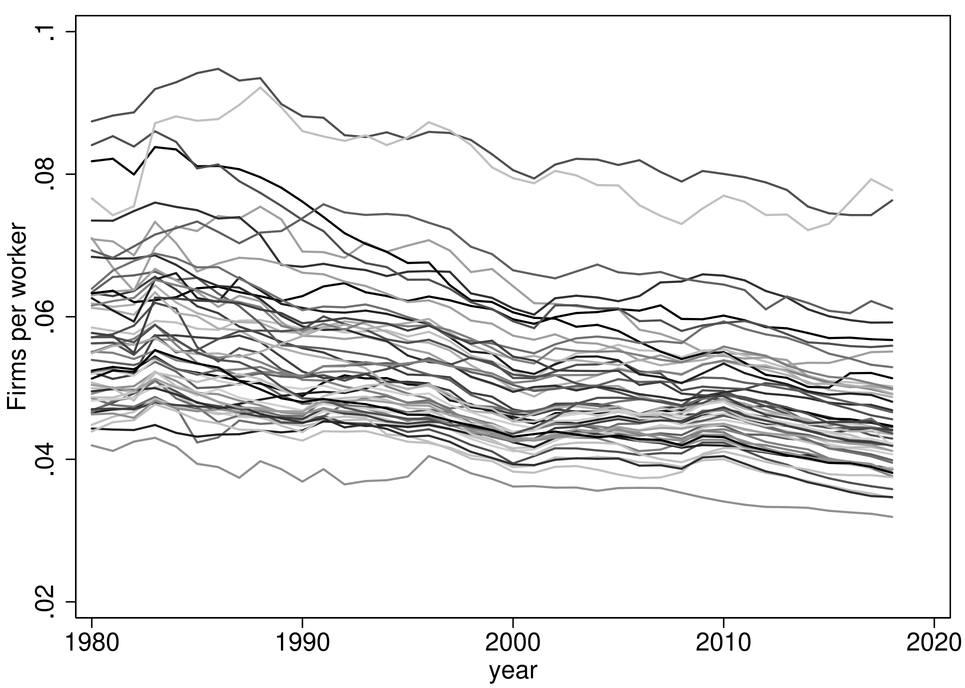
Figure (A1b) shows the average real wage, expressed as a fraction of the constant average productivity level, is increasing in the bargaining power of workers. As α rises, worker wages are increasingly determined by the match value of the incumbent employer and decreasingly tied to their outside option (i.e. the match value of the less productive prior employer). Therefore, a higher α increases the average wage as workers get a larger fraction of the joint match value. Figures (A1c) shows the wage growth associated with EE transitions as a function of α. With increased bargaining power, workers reach the upper limit of their maximum wage from a match. Thus, the extent of wage growth across (and within) jobs decreases with increasing α. In the extreme case when

α is one, workers get the entire match value, leaving no scope for within-job wage growth, and wages across jobs grow only to the extent of productivity growth. For workers at the higher rungs of the job ladder, the incidence of realizing a wage growth across jobs declines, and this depresses the average wage growth associated with EE transitions.

Finally, the model's equilibrium functions are omitted but behave as expected. The value functions of the employed and unemployed worker are increasing, whereas that of firms are decreasing in α. As the unemployed worker's value rises, she becomes pickier in the offers she chooses to forgo unemployment. This leads to an increase in her reservation productivity level with high bargaining power.

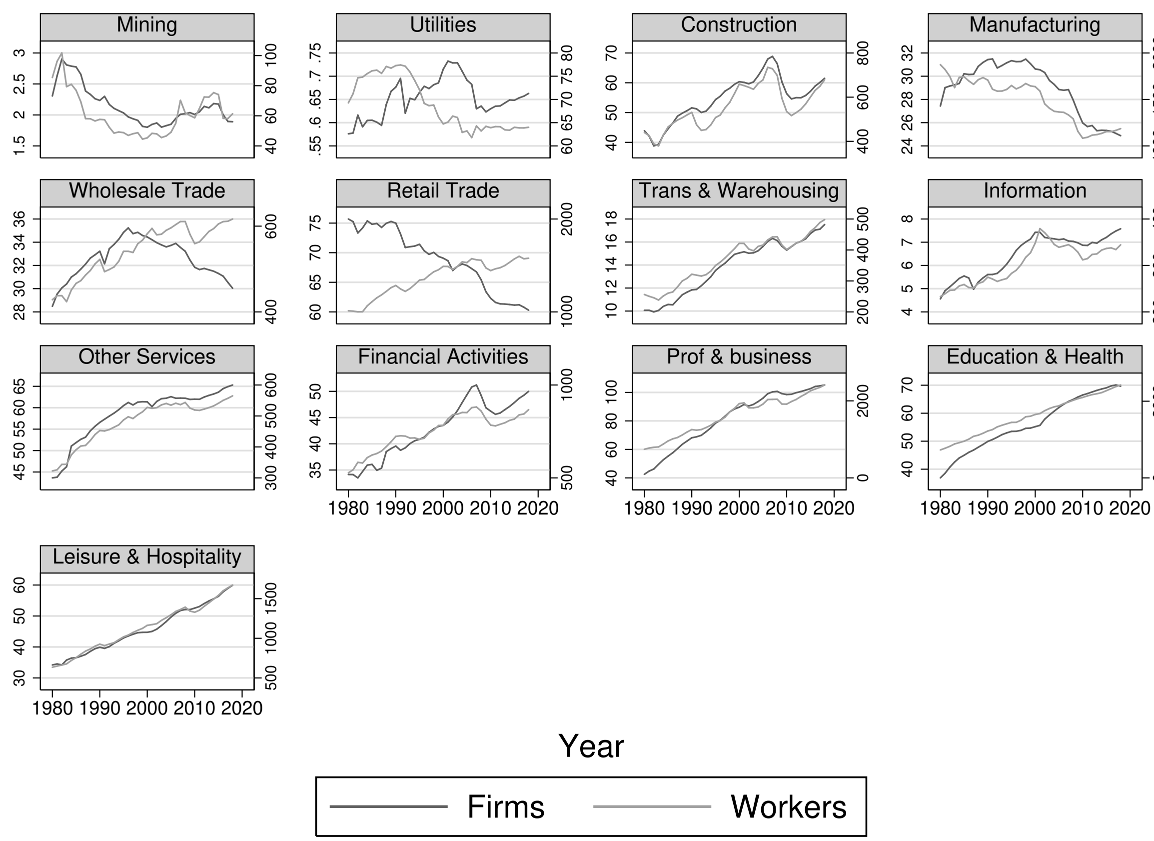
B Appendix Tables & Figures

Figure A2: 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.

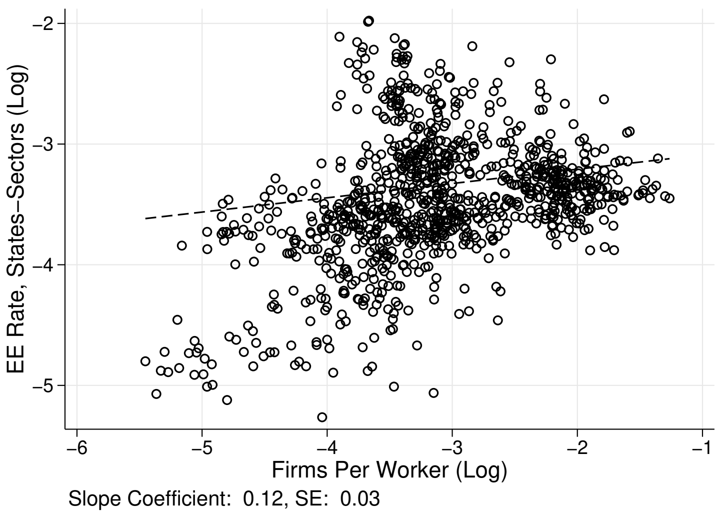
Figure A3: Number of Firms and Workers (in tens of thousands), 1979-2018



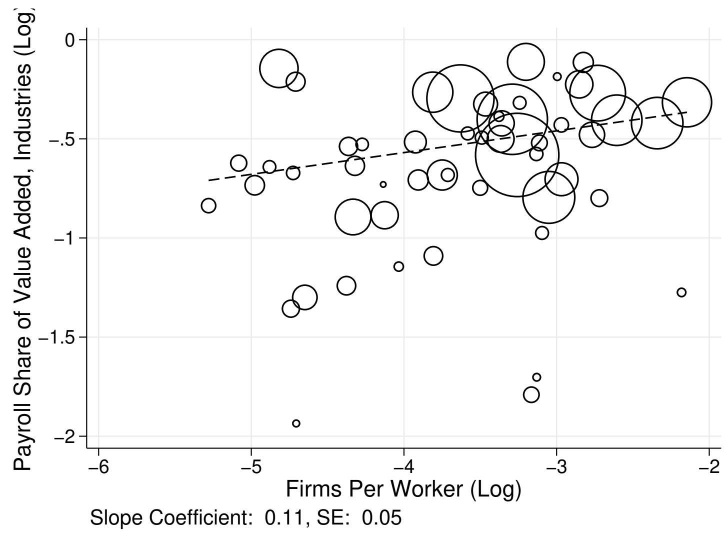
Notes: This figure plots the number of firms (left y-axis, in tens of thousands) and the number of workers (right y-axis, in tens of thousands) for each two digit NAICS sector of the US economy, over 1979-2018 using the Business Dynamics Statistics.

Figure A4: Cross-sectional Correlations in the Data

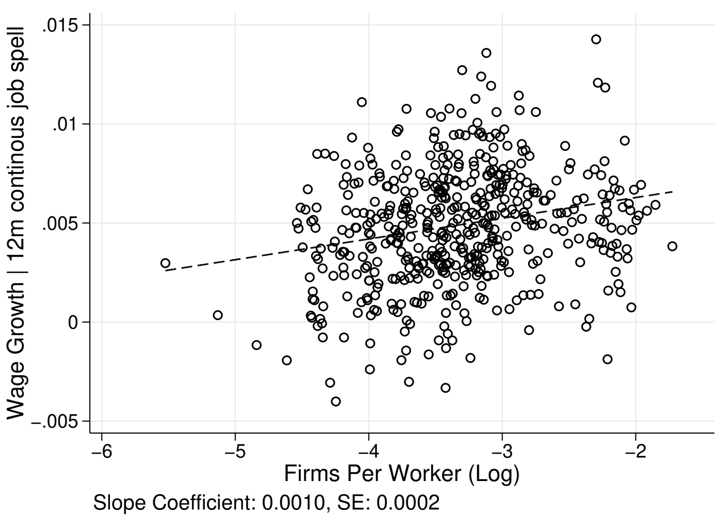
(a) EE transitions



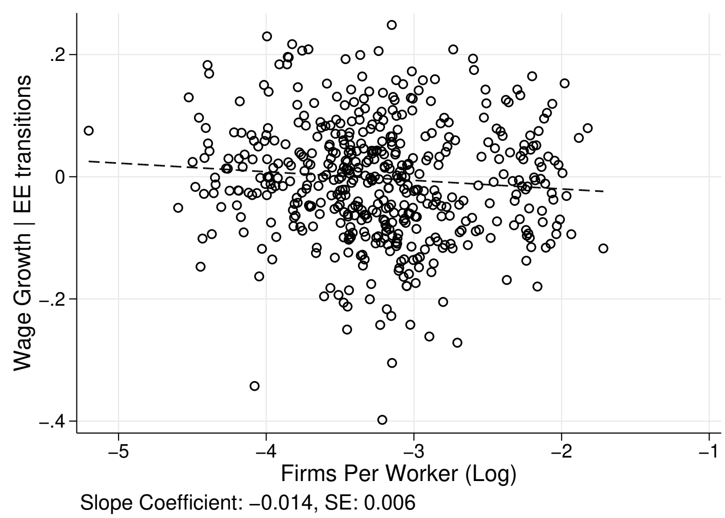
(b) Avg Wages, as a fraction of productivity



(c) Wage Growth, Stayers



(d) Wage Growth, Switchers



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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$