Firm Market Power, Worker Mobility, and Wages in the U.S. Labor Market*

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Abstract

A recent body of literature has documented evidence of increasing employer market power in the US. I develop an equilibrium model of the labor market to explain its effect on aggregate outcomes such as wage growth and job-to-job transitions. I introduce two ingredients to a random search model with on-the-job search: First, there is a finite number of employers who differ in their productivity. Second, employers exert market power by excluding their vacancies from the set of outside offers faced by their employees. The combined effect of both features of the model is to reduce the value of workers' outside options, thereby reducing wages and worker mobility in equilibrium. I calibrate the model and evaluate its performance in generating key labor market moments for the US economy. Finally, I examine the central predictions of the model using the publicly available data from the Longitudinal Employer-Household Dynamics (LEHD) and Business Dynamics Statistics (BDS). I document that less competitive labor markets, measured by a lower number of firms per worker, are associated with reduced measures of labor market dynamism and average wages.

JEL Classification: J31, J62, J42

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

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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, affects their opportunities to quit to better offers, even as employers become less aggressive to retain them. Overall, the model predicts that a declining number of firms in the relevant labor markets of workers is associated with a slowing of wages through 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 are closely tied to 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 2018, Schubert, Stansbury & Taska 2019) 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 wage growth 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 as a result of 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 (2019).

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 labor market flows, 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 vacancies from the outside offers of their employees, similar in spirit to Jarosch, Nimczik & Sorkin (2020). 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 market power 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 vacancy in the continuation value of the worker's outside offer. Removing such a vacancy discounts the outside offer of the worker, consequently putting downward pressure on the negotiated wage, and gives the winning firm more market power in the bargain.

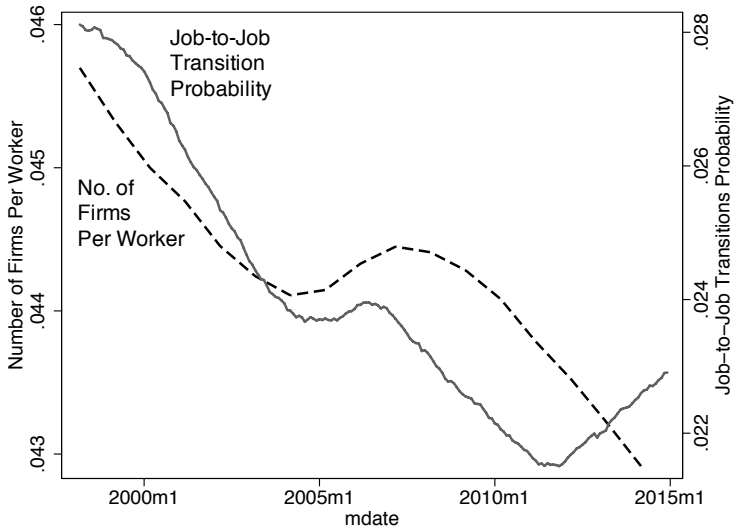
The model is calibrated to fit key moments of the US labor market. As part of the calibration, I show that the model can reproduce empirically observed labor market flows, including transitions from job-to-job, and into and out of employment, as well as the unemployment rate, and wage dispersion in the economy. I then undertake two counterfac-

tual exercises: In the first, I vary the number of firms in the economy and find that job flows, average wages (normalized by productivity), and worker's values derived in the model are increasing in 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. Second, by varying the bargaining power of workers, I find that average wages, market transitions, and worker value functions are increasing in their market power.

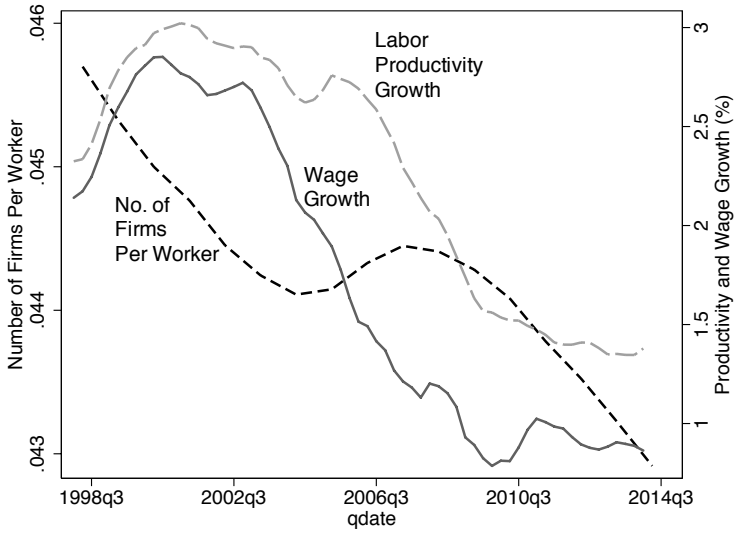
To evaluate the predictions of the model from an empirical standpoint, I examine the behavior of the model-relevant measure of labor market competition in the data. Specifically, I document trends in the number of firms, relative to the number of workers, in the US economy over the last four decades. 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 in the firms to worker ratio for the aggregate US economy. Figure (1) illustrates a snapshot of this decline from the late 1990s. 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 of worker mobility, and average wages. To illustrate this for the aggregate economy, Figure (1) also shows a concurrent decline from the late 1990s in not just the job-to-job transitions probability, but also the real wage growth, that has fallen beyond the measure of labor productivity growth. To formally examine this link, I combine data in the BDS with publicly available data on labor market flows, average wages associated with each type of flow, and worker-firm demographics from the Longitudinal Employer-Household Dynamics (LEHD). This yields an annual panel from 2000-2018, across sectors and Metropolitan Statistics Areas (MSAs). In line with the predictions of the model, two findings are noteworthy. One, I document a positive correlation between the number of firms per worker and labor market transitions – including those made from job-to-job, and into and out of employment – across local labor markets, using a rich set of fixed effects and controlling for workforce composition by the worker and firm demographic groups. Two, 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 vari-

Figure 1: Firms per Worker, Job-to-Job Transitions, and Real Wage growth



(a) Firms per Worker and Job-to-job Transitions



(b) Firms per Worker, Labor Productivity and Wage Growth

Notes: Firms per worker (left y-axis) are annual stocks of the number of firms and employees from Business Dynamics Statistics. Job-to-job transition probabilities (right y-axis) are monthly flows from Fujita, Moscarini & Postel-Vinay (2019) who use the Current Population Survey, and correct for missing observations after a survey methodology change in 2007. Wage growth (right y-axis) is the annualized quarterly growth in the hourly compensation deflated by the implicit price deflator. Labor productivity growth (right y-axis) is the annualized quarterly growth in output per hour. Wages and productivity are measured for the non-farm business sector from the Bureau of Labor Statistics (Elsby, Hobijn & Şahin 2013). Firms per worker, wage and productivity growth are ten-year MA, and job-to-job transitions are five-year MA.

ation 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 associated with each type of labor flow. Overall, the empirical evidence on labor market transitions and average wages is consistent with the predictions of the model.

The theoretical and empirical findings of this paper 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 (2020) consider finite firms in a standard Diamond-Mortensen-Pissarides model without on-the-job search, where firms can remove their vacancies from the outside options of unemployed workers. Two, and relatedly, Schubert, Stansbury & Taska (2019) 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. Thus, firms compete for employed and unemployed workers. This is motivated by recent work by Faberman, Mueller, Şahin & Topa (2017) 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 market-power based explanation to falling labor market dynamism, apart from falling wages, which much of the literature has already emphasized.

Other theoretical models studying imperfect competition in the labor market and its implications on average wages and labor share have introduced firm market power through different channels. Berger, Herkenhoff & Mongey (2019) 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 (2018) 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 that is 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. Hershbein, Macaluso & Yeh (2019) 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 (Autor, Dorn, Katz, Patterson & Van Reenen 2020), as well as Herfindahl Hirschman indices in employment (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 (2018) measure the cross-sectional competition faced by a worker from other similar workers across jobs to arrive at the worker's rele-

vant outside options. They find a positive correlation between outside options of German workers and their wages. Two, Schubert, Stansbury & Taska (2019) 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, and document a positive link between firm competition and labor market dynamism. 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 it's key features and their implications on the outcomes. Section 3 describes the calibration methodology, examines the model fit, and provides details of the counterfactual exercises. 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 discrete-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.

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 denoted by $\theta_i \in \{\theta_1, ..., \theta_N\}$. Assume that productivity is uniformly distributed across firms, and therefore, firms can be ranked by their productivity: $\theta_1 < \cdots < \theta_N$. At each productivity level, there are 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 post vacancies that are either filled or remain vacant. Filled vacancies grant firms the flow value of the output produced, less wages paid, and vacant postings give firms no value.

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

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 a vacancy arising from a firm with a productivity level θ_i is $n_i \cdot f(\theta_i)$.[4] On matching, firms and workers produce output equal to the firm's productivity. Matches are destroyed at an exogenous probability δ, in which case, the workers flow into unemployment and firms become vacant.

2.3 Wage Bargaining

On matching, workers and firms bargain over wages, with the worker's bargaining share 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's share is 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 has an outside option at another firm-$\theta_j \leq \theta_i$.[5] Wages, denoted by $\omega(\theta_i, \theta_j)$, are negotiated between firm-θ_i and the worker based on her outside option.[6] 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 $\theta_x > \theta_i$. 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 outside option-θ_j, and can be denoted as $\omega(\theta_i, \theta_i) = \theta_i$. From the new wage, the worker derives the entire match value,

[4] With the normalization that $\sum_{i=1}^{N} n_i f(\theta_i) = 1$

[5] Note, even though I describe the example for an employed worker, it includes the case of an unemployed worker under the assumption that $\theta_j = \theta_1$. This is discussed later in the section.

[6] The exposition of the model is similar to Jarosch (2015).

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

$W(\theta_i, \theta_i) = V(\theta_i)$. This comprises her new outside option when negotiating wages with the poaching firm-θ_x. The resulting wage offered by the poaching firm, $\omega(\theta_x, \theta_i)$, leaves the worker with a value equal to her new outside option, and $\alpha-$share of the increment in the joint match value that results from the worker quitting the less-productive incumbent firm, and joining the more productive poaching firm:[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 $\theta_j < \theta_x \leq \theta_i$. 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. 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 matched with 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 outside offer from firm-θ_j. The latter includes the flow value from the previous 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 again, making the worker's outside option contain, with non-zero probability, a future match with firm-θ_i. Thus, while negotiating wages, firm-θ_i competes with the possibility of its own future vacancy matching with the worker again.

[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.

In a finite firm framework where each firm has a positive vacancy share, I assume that firm-θ_i is allowed to remove its future vacancy 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 (2020), I assume that firms do not allow already matched applicants to reapply.[9] In other words, should the wage negotiation between the worker and firm-θ_i break down on matching, and the worker avails her outside option at firm-θ_j, then she cannot receive the option value of matching with firm-θ_i again through an 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, the mechanism affects the equilibrium outcomes of the model such as wages and worker flows. 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 as $\widetilde{W}(\theta_j, \theta_j, \theta_i)$, i.e., the value offered by firm-θ_j is equal to the flow output θ_j, and option value from on-the-job search, with the exclusion of an offer from firm-θ_i. 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. The value of an unemployed worker entails 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 vacancies from outside options of 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 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 such that the worker is indifferent between staying unemployed or employed at firm-θ_u. Thus, the value received by a worker hired

[9]Note that it is optimal for the firm to not make an offer to the penalized worker if that worker is not the sole applicant who matches with the firm. I assume that the probability of the firm matching with that particular worker is approximately zero. Jarosch et al. (2020) compute this probability from matched employer-employee data from Austria and find it to be very small.

from unemployment by firm-θ_i is a linear combination of her outside option from unemployment, excluding the option value of matching with firm-θ_i, and the net increment in joint value from 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:

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

The employed worker receives a flow payoff equal to the current wage, $\omega(\theta_i, \theta_j)$. Next period, which is discounted at β, 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 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, otherwise she stays at θ_i. 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. I assume that the worker stays at the incumbent firm.[10] With the remaining probability she does not match with any firm, or matches with a firm that is less productive than θ_j, and her value is unchanged.

Now suppose a worker who is employed at θ_i, gets an on-the-job offer from some firm-

[10] This is a simplifying assumption. As a result of this, I derive a lower bound of all job-to-job transitions that this worker can potentially make.

$\theta_h > \theta_i$. Then the worker's outside option, denoted by $\widetilde{W}(\theta_i, \theta_i, \theta_h)$, can be expressed as:

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

To retain the worker, firm-θ_i bids up the wage to its maximum level, such that the worker gets the entire match output. As a result, there is no longer a scope for a within-job wage raise and the worker value ceases to be a function of θ_j. The option value of search excludes the possibility of sampling a job from a firm with productivity θ_h. This is shown in the second 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 assumption is made to avoid keeping track of the history of precluded firms' from the worker's offer distribution.

The value function of an unemployed worker satisfies:

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

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 the firm at the threshold productivity level, θ_u, the worker accepts the job and flows into employment.[11] With the remaining probability, the worker does not accept a job offer and 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

[11] As noted above, 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 productivity θ_u (and receive the entire match value). Thus, $U = V(\theta_u)$. 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. I assume there is a single firm at the reservation productivity level, i.e., $n_u = 1$.

a firm with productivity θ_h. The outside option can be expressed as:

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

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.[12]

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

$$\begin{aligned}J(\theta_i, \theta_j) = \theta_i - \omega(\theta_i, \theta_j) + \beta(1-\delta)\Bigg[\lambda_1 \sum_{x=j+1}^{i-1} J(\theta_i, \theta_x) n_x f(\theta_x) \\ + \Bigg(1 - \lambda_1 \sum_{x=i+1}^{N} n_x f(\theta_x) - \lambda_1 \sum_{x=j+1}^{i-1} n_x f(\theta_x) - \lambda_1 (n_i - 1) f(\theta_i)\Bigg) J(\theta_i, \theta_j)\Bigg]\end{aligned} \tag{9}$$

The flow payoff to the firm is equal to the output, θ_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.[13]

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.

[12] 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.

[13] Note that throughout the model, the value of keeping a job opening vacant is assumed to be zero. In a model with finite firms and no free entry, this condition can be achieved by assuming that the cost of posting a vacancy to a firm is firm productivity- and worker outside option- specific. With this assumption, the entire model can be solved without the need to specify the value of a vacant posting.

2.5 Solving the Model

The value functions in equations (5)-(9), along with solutions to Nash bargaining in (3) and (4) can be combined into one functional equation – the surplus function – defined as the match value net of the value from unemployment, $\widetilde{S}(\theta_i, \theta_h) = \widetilde{W}(\theta_i, \theta_i, \theta_h) - \widetilde{U}(\theta_i), \forall h > i$.[14] When $h = i$, the surplus function takes the form: $\widetilde{S}(\theta_i, \theta_i) \equiv S(\theta_i) = \widetilde{W}(\theta_i, \theta_i, \theta_i) - \widetilde{U}(\theta_i) \equiv V(\theta_i) - \widetilde{U}(\theta_i)$. The derivation of the surplus function is detailed in Appendix A.2, and the result is stated below, $\forall h \geq i$:

$$\begin{aligned}
\widetilde{S}(\theta_i, \theta_h) = \theta_i + \beta \Bigg\{ & \delta(U - \widetilde{U}(\theta_i)) \\
& + (1-\delta) \Bigg[\lambda_1 \sum_{x=i+1}^{N} \Big((1-\alpha)\widetilde{S}(\theta_i, \theta_x) + \alpha S(\theta_x) + \alpha(\widetilde{U}(\theta_x) - \widetilde{U}(\theta_i)) \Big) n_x f(\theta_x) \\
& - \lambda_1 \Big((1-\alpha)\widetilde{S}(\theta_i, \theta_h) + \alpha S(\theta_h) + \alpha(\widetilde{U}(\theta_h) - \widetilde{U}(\theta_i)) \Big) f(\theta_h) \\
& + \lambda_1 S(\theta_i)(n_i - 1) f(\theta_i) \\
& + \Big(1 - \lambda_1 \sum_{x=i+1}^{N} n_x f(\theta_x) + \lambda_1 f(\theta_h) - \lambda_1 (n_i - 1) f(\theta_i) \Big) \widetilde{S}(\theta_i, \theta_h) \Bigg] \Bigg\} - (1-\beta)\widetilde{U}(\theta_i)
\end{aligned} \tag{10}$$

with $\widetilde{S}(\theta_u, \theta_u) = 0$.

The left-hand side is the surplus from a match, or the net 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 joint value function nets the value from unemployment forgone by the worker, which does not include an offer from firm-θ_i.

The first term on the right-hand side captures the flow payoff from the match to the worker and firm, θ_i. The second term captures the event of the match coming to an end, and the worker receiving the net gain from facing a value from unemployment that now includes the option value of search at firm-θ_i. The terms on the second and third lines 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. In the latter case, the worker receives value equal to the weighted average of the surplus from the poaching and incumbent firms, as well as the net change in unemployment value that now excludes an offer from the poaching instead of the incumbent firm. The term on the fourth line captures the possibility of the worker receiving an offer from

[14] The surplus function $\widetilde{S}(\theta_i, \theta_h)$ is defined in terms of $\widetilde{U}(\theta_i)$ and not U. This is because when the worker is employed at θ_i, her outside option from the state of unemployment would preclude the possibility of an getting an offer from θ_i. Thus, she would face an unemployment value of $\widetilde{U}(\theta_i)$ instead of U.

any 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 first term on the last line captures the event of the match continuing on current terms if the worker does not receive a job offer, or receives one from firm-θ_h. The last term captures the value from unemployment that is forgone by the worker while she is employed at firm-θ_i.

I show in Appendix A.2 that the unemployment functions U and $\widetilde{U}$ can also be expressed in terms of the surplus function. This allows the surplus function to be expressed as a functional equation, making the model tractable. The model can be fully summarized by two equations (equation (10) and $\widetilde{S}(\theta_u, \theta_u) = 0$) and two unknowns ($\widetilde{S}$ and θ_u), and can be solved as a system of linear equations. The algorithm of solving the model numerically is detailed in Appendix A.3. Finally, the equilibrium wage function is derived in Appendix A.4.

3 Calibration

I solve the model described in the previous section and simulate its equilibrium outcomes. In what follows, I first describe the empirical moments that are targeted in the calibration exercise and discuss how they are informative about the parameters of the model. As the model is the same in and out of steady-state, the parameter values are chosen such that the equilibrium outcomes of the model match the long-run empirical moments of the US economy. This is followed by a comparison of the simulated moments at the optimally chosen parameter values and their empirical counterparts to assess the fit of the model. Finally, I show two counterfactual exercises varying key parameters of the model - the number of firms in the economy, and the bargaining power of workers - while holding the other parameters at their optimal values.

3.1 Methodology

The model is calibrated at a monthly frequency. The discount factor, β, is set to match an annual interest rate of five percent. The flow payoff of leisure, z, is chosen to target 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; Hall & Milgrom (2008), 0.71 and Hagedorn & Manovskii (2008), 0.995).

The contact probability of the employed (λ_1) and unemployed (λ_0) are positively related to 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, is informative about the employment-to-unemployment (EU) flow probability and the resulting unemployment rate, and is chosen to match the latter.[15] Following the methodology of Shimer (2012), Moscarini & Postel-Vinay (2018) estimate the long-run averages of the UE and EU transition probabilities utilizing stocks of unemployment duration from the monthly Current Population Survey (CPS) from 1990-2018.[16] They arrive at a monthly EU separations probability of 2.4%, and UE hires probability, averaging to 41%. The steady-state unemployment rate is computed at the monthly frequency by taking a ratio of the separation probability and the sum of separation and hire probability, and averages to 5.7%. The 1994 re-design of the CPS introduced dependent interviewing, allowing for the computation of steady-state EE transition probability at around 2%.

Next, I set the job offer distribution to be lognormal with mean 0 and standard deviation, σ_θ. The productivity levels of firms in the model are in the same space as wages, with the maximum wage of a match being equal to the output or the productivity level of the firm. Thus, the variance of the offer distribution, σ_θ, is set to target the standard deviation of offered wages estimated by Hall & Mueller (2018). The latter is computed by using panel data on job seekers drawing unemployment benefits in New Jersey in 2009 (Krueger-Mueller Survey) and estimated, after controlling for the job seeker's productivity, at 0.24.

The number of firms in the model reflects the relevant labor market of the worker. Whereas there is no perfect measure for this, a potential moment for identifying the number of relevant firms in a worker's labor market is the average number of applications filed by employed and unemployed job seekers. There are at least two recent attempts in the literature to measure such a moment. One, Faberman & Kudlyak (2019) measure all applications made by job seekers to vacancies on a private online job search engine between September 2010-2011. The vacancies are predominantly in hourly, less-skilled jobs in the retail and service sector. They find that the average job-seeker filed 7.1 applications per month. Two, Marinescu & Rathelot (2018) utilize data on users with active accounts and vacancies posted on another online job board between April and June 2012. While the vacancies on the job portal comprised more than a third of all vacancies posted in the US

[15] The results are quantitatively similar if I alternatively target the average monthly EU transitions probability.

[16] Monthly EU separation probability is computed by taking a ratio of the number of workers who were unemployed for less than a month, to the total employment counts of the previous month. The monthly UE hire 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 previous month to the current month, and divided by the number of unemployed workers in the previous month.

Table 1: Calibrated Parameter Values

	Parameter	Value	Identifying Moment
λ_0	Contact probability of unemployed	0.7022	E[UE]
λ_1	Contact probability of employed	0.4351	E[EE]
δ	Separation probability	0.0250	E[U]
σ_θ	SD of job offer distribution	0.2640	SD(wages)
z	Flow value of leisure	0.9335	z/ALP
$N \times n$	Number of firms	7 ($N = 7, n = 1$)	Avg. applications per job seeker
α	Bargaining power of worker	0.5	Benchmark
β	Discount factor	0.9959	5% annual real interest rate

Notes: This table displays the calibrated parameter values of the model, when the model is simulated at monthly frequency. E[UE] stands for average unemployment-to-employment flows, E[EE] stands for average employment-to-employment flows, and E[U] stands for average unemployment rate, all computed at a monthly frequency and averaged over a long-run horizon. SD(wages) refers to standard deviation of offered wages, and z/ALP stands for the flow value of leisure as a fraction of the average labor productivity of the economy.

in January 2011, they over-represent certain industries such as information technology, finance, and real estate sectors. More importantly, the authors only looked at the sample of unemployed users of the job portal and observed that the average unemployed job seeker filed around 12.8 applications in a month. Since the model presented in this paper includes job search by the unemployed and employed, I use the measure by Faberman & Kudlyak (2019), and set the number of firms in the model to 7.[17] Finally, the bargaining power of the worker, α, is benchmarked at 0.5.

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 exactly identified in that five moments (averages of unemployment-to-employment and employment-to-employment transitions, unemployment rate, the standard deviation of offered wages, and flow value of leisure as a fraction of average labor productivity) are used to identify five parameters $(\lambda_0, \lambda_1, \delta, \sigma_\theta, z)$. More details of the simulation and calibration methodology are given in the Appendix.

Table (1) shows the model parameters that minimize the distance between the empirically targeted and model-generated moments. Table (2) displays the simulated moments

[17] I assume each productivity level has the same number of firms. Thus, the total number of firms in the model is $n \cdot N$. In the baseline calibration, I assume there are 7 productivity levels and one firm at each level. This does not include θ_u which is always a single firm.

Table 2: Data and Model-generated Moments

Moment	Data	Model	Data Source
E[EE]	0.0200	0.0215	Moscarini & Postel-Vinay (2018)
E[UE]	0.4100	0.4136	Moscarini & Postel-Vinay (2018)
E[U]	0.0570	0.0568	Moscarini & Postel-Vinay (2018)
SD(wages)	0.2400	0.2567	Hall & Mueller (2018)
z/ALP	0.6000	0.5992	Hagedorn & Manovskii (2008)

Notes: This table displays the model-simulated moments and their empirical counterparts, where the latter are targeted to arrive at the optimal parameter values. E[UE] stands for average unemployment-to-employment flows, E[EE] stands for average employment-to-employment flows, and E[U] stands for average unemployment rate, all computed at a monthly frequency and averaged over a long-run horizon. SD(wages) refers to standard deviation of offered wages, and z/ALP stands for the flow value of leisure as a fraction of the average labor productivity of the economy.

of the model and their empirical counterparts at the calibrated parameter values. Overall, the model matches the targeted moments well. The average EE and UE transition probabilities are slightly higher, resulting in the average unemployment rate being slightly lower.[18] The standard deviation of offered wages is also higher in the model, but close to the data. The flow value of leisure, as a fraction of ALP, yields the value of z to be close to the one estimated in Hagedorn & Manovskii (2008).

The next section presents two counterfactual exercises. In the 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 equilibrium functions and various moments of the model.

3.2 Results

3.2.1 Changing competition among firms

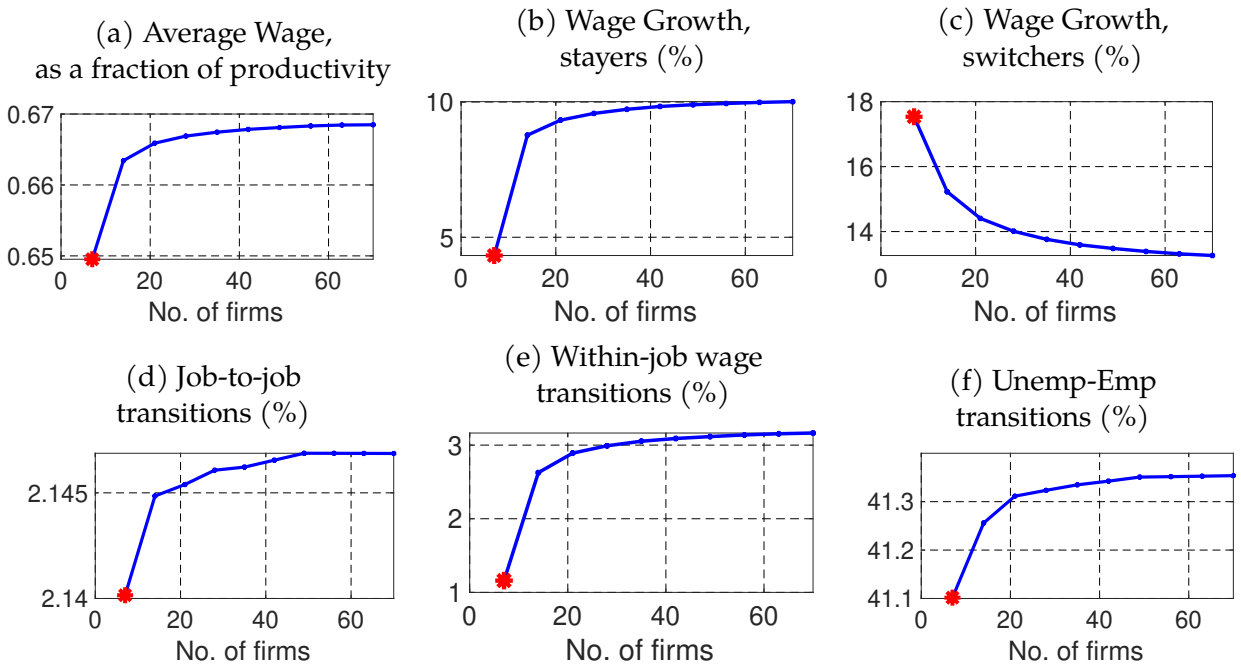
Figure (2) plots wage and labor flow moments generated by the model with changing competition among firms for workers. In particular, I hold the number of firm productivity levels fixed, and all parameters of the model at their calibrated values, and only vary the number of firms within each productivity level, n, from it's calibrated value denoted by the red star.[19]

Panel (2a) shows that the average real wage, expressed as a fraction of the constant

[18] The model-generated UE transition probability also comes very close to the data.

[19] Note that number of productivity levels (N) is held fixed. The reason for introducing multiple firms at each productivity level is to hold productivity levels constant across different specifications of n.

Figure 2: Response of wages and labor flows to changing number of firms



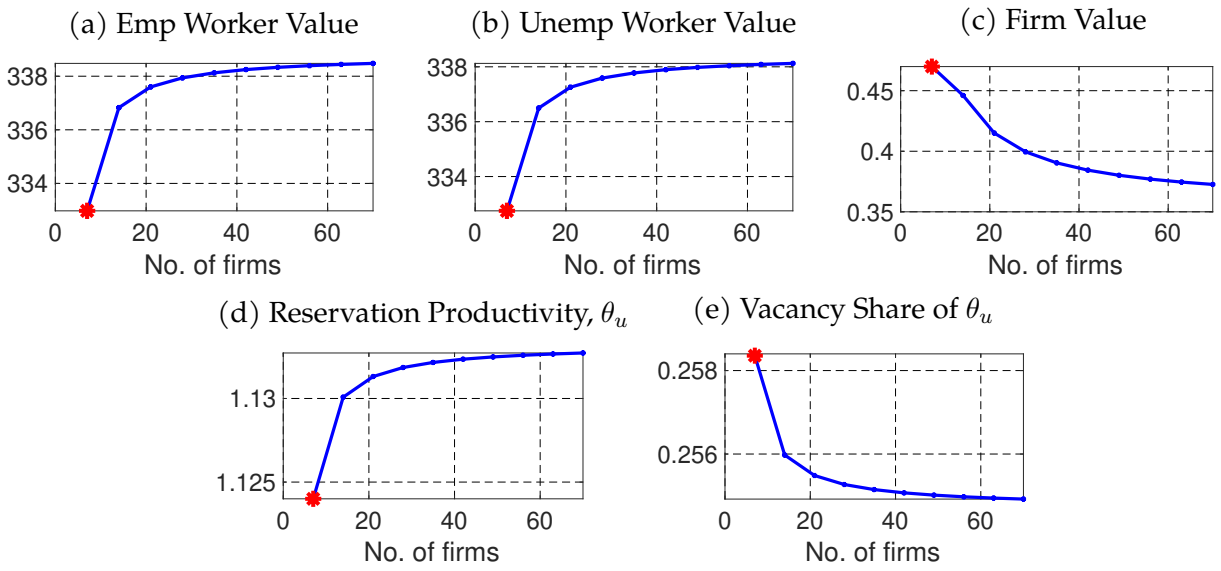
Notes: This figure displays the model-simulated moments in response to different values of n, holding all other parameters fixed at their calibrated values in Table (1). The point in red denotes the model at the calibrated value of n. The x-axis of each panel denotes the number of firms at all productivity levels, holding the number of productivity levels constant.

average productivity level of the economy, increases with the number of firms. When there are many firms in the market, each firm has a lower vacancy share and the market converges towards one with atomistic firms. This diminishes firms' ability to penalize their employees by removing their vacancies from their outside options. Thus, competition intensifies as firms try to poach and retain workers, increasing the outside options of workers. This results in a bidding up of wages.

The growth rate of wages within and across jobs are shown in panels (2b) and (2c). As competition in the economy increases, workers are more likely to get an offer from a firm at the same productivity level. Incumbent firms, in trying to match the offers of poaching firms, offer the maximum wage to retain the workers. As a result, workers increasingly get a within-job wage increase as employer competition increases, explaining the rising wage growth of job stayers. At the same time, the likelihood of maxing out on their wage while they are in the same job also increases. As a result, wage growth while switching jobs decreases.

Panels (2d) to (2f) plot the behavior of labor market flows with increasing number of firms in the model. When competition in the economy rises, the job-to-job and unemployment-

Figure 3: Response of equilibrium functions of the model to changing number of firms



Notes: This figure displays the model's equilibrium functions in response to different values of n, holding all other parameters fixed at their calibrated values in Table (1). The point in red denotes the model at the calibrated value of n. The x-axis of each panel denotes the number of firms at all productivity levels, holding the number of productivity levels constant. Employed worker value and firm value functions correspond to the firm's productivity of θ_2, and worker's outside option of θ_u. Unemployed worker's value function is U.

to-employment transitions increase. The intuition behind this can be understood in two ways: First, as the outside options of workers contain more firms, the probability of getting an offer from firms at higher productivity levels increases. Thus, workers increasingly climb the job ladder and transition out of unemployment. Two, normalizing the job offer distribution across all firms to one, as competition increases, unemployed workers become pickier and their reservation productivity level increases (shown below). As a result, the probability associated with getting an offer from the firm at the reservation productivity level decreases, and the mass of the job offer distribution shifts to firms at all other productivity levels. This increases transitions from unemployment to employment as well as job-to-job. Panel (2e) shows an increase in within-job wage transitions or "job promotions". As the competition intensifies, the probability of getting an offer from a firm at the same productivity level increases. Thus, worker outside options, against which their wages at the incumbent employer are benchmarked, is updated frequently which leads to an increase in wage transitions within jobs.[20]

Figure (3) shows the response of the equilibrium functions of the model to a higher number of firms in the economy. For demonstration, all functions are plotted for a worker

[20]Note that the preclusion of offers from a worker's outside option does not affect labor market flows because the former happens off-equilibrium, and flows are equilibrium outcomes.

hired from unemployment to a firm with productivity-θ_2. Panels (3a) to (3c) show that as competition in the economy intensifies, the value to the employed and unemployed worker increases, while that to the firm reduces. As firms become increasingly atomistic, their ability to discount the outside options of workers diminishes. As the outside options of workers grow, they receive a larger split of the match value, resulting in high worker- and lower firm-value. Thus the joint value of match is increasing in the number of firms, as employed worker's value increases more than the reduction in firm value.

Panel (3d) plots the unknown reservation productivity level of the worker. As competition in the economy increases, firms are less able to penalize unemployed workers by removing their vacancies from their outside options, thereby increasing the option value of search from the state of unemployment. 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. Finally, panel (3e) shows that with a log-normal offer distribution, the vacancy share of the firm at θ_u decreases with increasing θ_u as a result of an increasing number of firms. This results in the mass of the vacancy distribution being shifted to all other productivity levels.

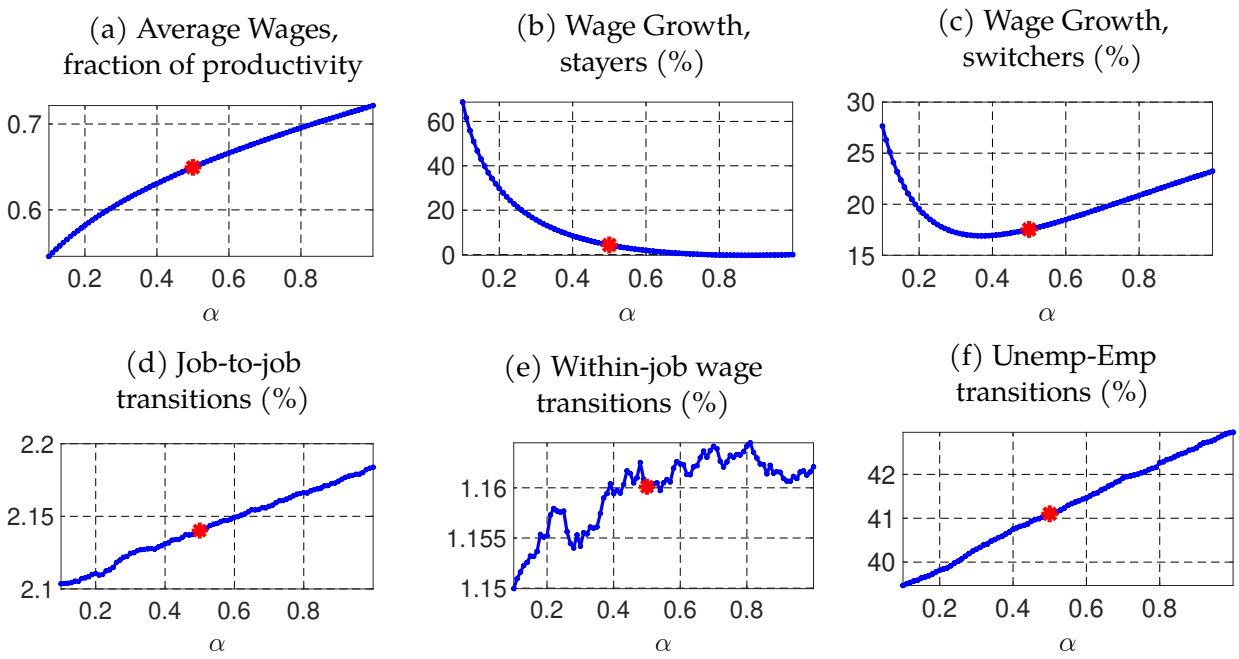
3.2.2 Changing bargaining power of workers and firms

Figure (4) shows the response of the model moments with the varying bargaining power of workers, α, holding all other parameters of the model constant, and with the red star denoting the calibrated value of α.

Panel (4a) shows the average real wage, expressed as a fraction of constant average productivity level, is increasing in the bargaining power of workers. As α increases, worker wages are increasingly determined by match value and decreasingly tied to their outside option. Therefore, an increase in α increases the average wage as workers get a larger share fraction of the joint match value. Panels (4b) & (4c) show the wage growth of job stayers and job switchers, respectively. With increased bargaining power, workers reach the upper limit of their maximum wage. Thus, the extent of wage growth within jobs decreases with α. In the extreme case when α is one, workers get the entire match value, leaving no scope for within job wage growth. Wage growth across jobs follows a U-shape. As α approaches it's lowest or highest values, wages become tightly linked to the match output of the worker's prior or current match, respectively. Job-to-job switches in which wages rise from one point on the grid of the productivity distribution to another entail a larger wage jump on average than ones in which wages rise to points off the grid. Thus, wage growth across jobs are increasing when α takes on extreme values and decreasing otherwise.

Panels (4d) to (4f) show that worker transitions are increasing in α. As the bargaining

Figure 4: The response of wages and labor flows to changing the bargaining power of workers

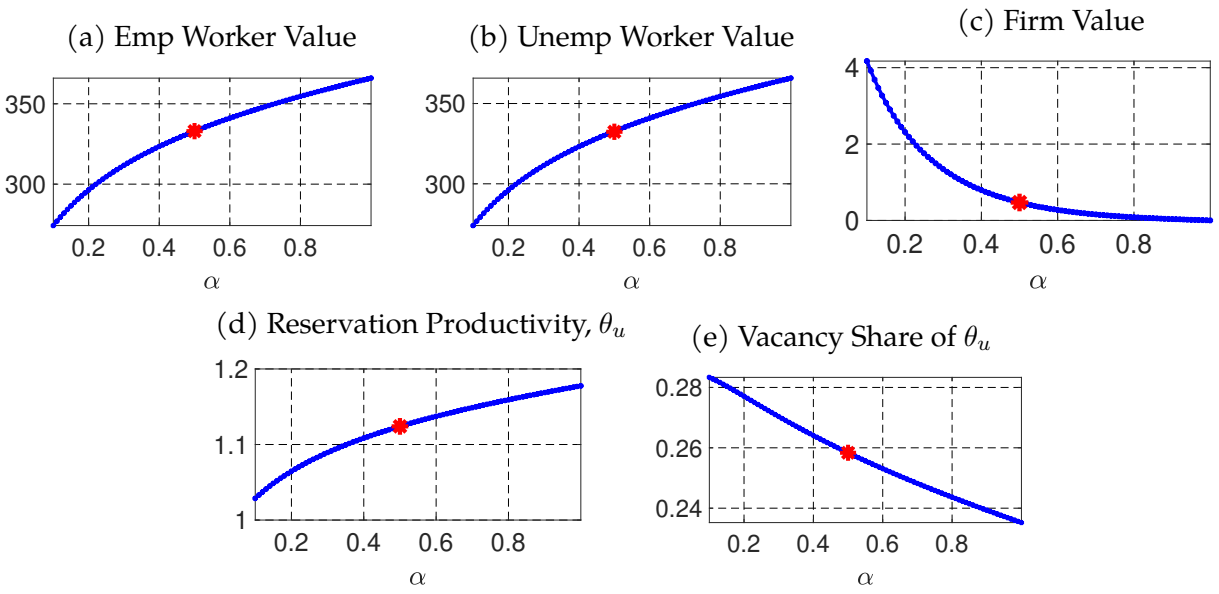


Notes: This figure displays the model-simulated moments in response to different values of α, holding all other parameters fixed at their calibrated values in Table (1). The point in red denotes the model at the calibrated value of α.

power of an unemployed worker increases, she becomes increasingly pickier, leading to an increase in her reservation productivity level. Thus, the mass of the offer distribution shifts from the lowest productivity level to higher ones. As a result, workers increasingly climb the job ladder and job-to-job, and unemployment-employment transition probability increases. Within-job transitions also increase but to a much lower extent than across-job transitions.

Finally, Figure (5) shows the response of equilibrium functions of the model to varying bargaining power of workers and firms. Rising α corresponds to the higher market power of workers, and lower market power of firms in the match. Again, all value functions are plotted for a worker-firm match, where the firm's productivity level is θ_2, and the worker's outside option is θ_u. As expected, panels (5a) to (5c) show that the value functions of the employed and unemployed worker are increasing, whereas that of firms are decreasing in α. Panels (5d) & (5e) show that as the unemployed worker's value increases, she becomes pickier in the offers she chooses to accept to forgo unemployment. This leads to an increase in her reservation productivity level and a decrease in the associated vacancy share.

Figure 5: Response of equilibrium functions of the model to changing bargaining power of workers



Notes: This figure displays the model's equilibrium functions in response to different values of n, holding all other parameters fixed at their calibrated values in Table (1). The point in red denotes the model at the calibrated value of n. The x-axis of each panel denotes the number of firms at all productivity levels, holding the number of productivity levels constant. Employed worker value and firm value functions correspond to the firm's productivity of θ_2, and worker's outside option of θ_u. Unemployed worker's value function is U.

4 Number of Firms Per Worker, Job Flows and Wages

The model presented in the previous section primarily hinges on the finiteness of firms as a source of their market power. Empirically, this translates to the number of employing firms in a labor market of a given size. 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 to better offers, resulting in a high rate of job-to-job transitions. Two, increased efforts of firms to retain workers, resulting in higher average wages. For the non-employed workers, a higher number of firms would imply a rise in the rate of non-employment to employment transitions, and higher reservation wage as workers sample vacant jobs at firms with increased likelihood. In this section, I attempt to empirically examine these predictions of the model.

I first document 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.[21]

[21]The precise 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

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.[22] 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 predictions of the model by examining the association between firms per worker and the different model-relevant outcomes in the data, such as the pace of job flows and the average wages associated with them. I provide descriptive evidence of the model's mechanism linking declining dynamism, 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

To measure the effect of the number of firms per worker on the pace of job flows and average wages, I use data from three sources. 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 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 labor market 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 pro-

by the number of employer-firms (i.e., excluding non-employee firms from the sample) which is available from the early 1980s.

[22] 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 number of firms per employee, the more intense is firm competition for workers. Furthermore, without including unemployed workers or nonparticipants, the firms to worker ratio act 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.

grams. 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, worker flows into and out of employment, along with average wages associated with each type of transition. Like the BDS, disaggregated data is available by regions and industries, but unlike the BDS, all states do not enter the LEHD program at the same time, with the earliest states' data available starting from 2000.

Finally, 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 enter 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.

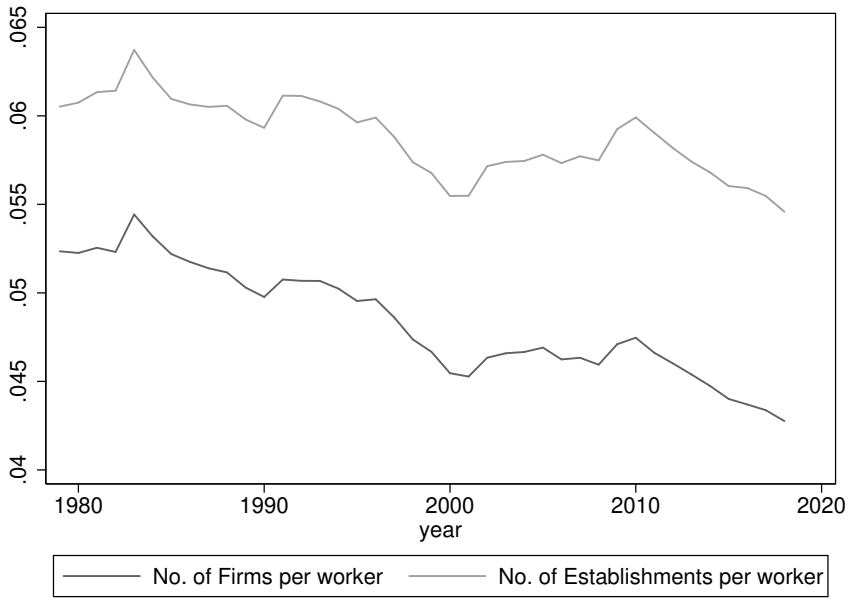
Combining the three data sources yields an annual panel over the sample period 2000-2018, with states entering the data at different times. The main variables of interest are measures of firms per worker, job flows, average wages, and employment composition by worker-age and education groups, and firm-age 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 sectors over 19 years, yielding 124,750 sector-MSA-year observations.

4.2 Evolution of Firms per Worker in the US Economy

I first focus on the number of firms, establishments, and workers for the aggregate US economy. Figure (6) plots trends in firms- and establishments- per worker from 1979-2018. Two observations are immediately apparent. 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 increasing 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.[23] Two, the declines were especially sharp in periods of 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

[23]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 (Hershbein, Macaluso & Yeh 2019).

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



Notes: This figure shows 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.

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 is a result of changing employment composition across sectors 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 (3) 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 are the only sectors that see an increase in the ratio over time. A closer inspection into the trends in the levels of firms and workers plotted in Figure (A2) in the Appendix reveals that the decline in firms could not keep pace with labor reallocating away from these sectors. As a result, these sectors experienced an

Table 3: Firms per Worker by sector and time-period, 1984-2018

	1984-88	**1995-99**	**2003-07**	**2014-18**
Mining (21)	0.038	0.041	0.036	0.031
Utilities (22)	0.008	0.010	0.011	0.010
Construction (23)	0.098	0.103	0.094	0.094
Manufacturing (31-33)	0.018	0.019	0.021	0.022
Wholesale Trade (42)	0.067	0.063	0.057	0.051
Retail Trade (44-45)	0.065	0.050	0.044	0.039
Trans & Warehousing (48-49)	0.040	0.038	0.037	0.036
Information (51)	0.021	0.022	0.021	0.022
Financial Activities (52-53)	0.057	0.057	0.057	0.058
Prof & business serv (54-56)	0.058	0.052	0.050	0.045
Edu & health (61-62)	0.045	0.036	0.033	0.030
Leisure & Hosp (71-72)	0.047	0.041	0.038	0.036
Other serv (81)	0.132	0.122	0.116	0.117

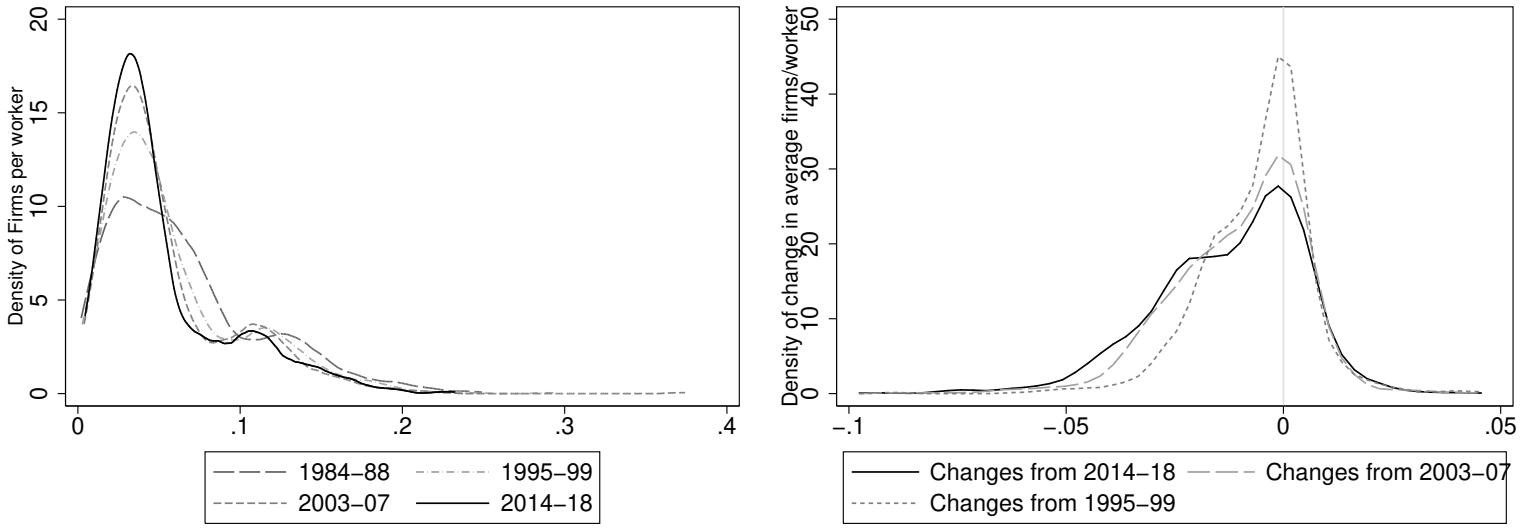
Notes: This table displays the long-run averages of firms to worker ratio for each sector, using the Business Dynamics Statistics. Two-digit NAICS sectors are listed in parenthesis.

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 decline 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 decline in the firm to worker ratio, except Information and Finance that did not experience much of a change. I conclude that the aggregate decline in Figure (6) was not a result of labor reallocating away from shrinking sectors with higher numbers of firms per worker to growing ones with lower levels of the same.[24]

The aggregate decline in firms per worker was also not a result of shifting employment composition across different regions. Figure (A1) in the Appendix plots the firms to worker ratio for all states over the sample period, and shows the decline is pervasive across all states. Finally, to understand the evolution of the ratio within both states and sectors, Figure (7) panel (a) plots the distributions of long-run averages of firms per worker across state-by-sector cells for different periods. Notice that in each subsequent sub-period starting from 1984-88 to 2014-18, the distribution of firms per worker has shifted towards zero,

[24]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 7: Firms per Worker by state-sector pairs and time-period, 1984-2018



(a) Density of firms per worker

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

Notes: Panel (a) of this figure plots the density of long-run averages of firms per worker across the state two-digit NAICS sector pairs for four time-periods. The distributions are truncated at 0.4. Panel (b) plots the change in density of each time-period of Panel (a) relative to 1884-88. The distributions are truncated at -0.1 and 0.05. Both panels use data from the Business Dynamics Statistics.

with a higher mass on lower values. Panel (b) plots the same distributions of firms per worker across state-by-sector cells as in panel (a) but expressed in terms of changes relative to their counterpart in 1984-88 which is denoted by the vertical line at zero. Similar to the observation in panel (a), notice that in panel (b) 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 economy, as well as within sectors, states, and a majority of sector-by-state cells. In the next section, I show that this decline, which I argue is a proxy for labor markets becoming less competitive over time, is closely tied to the pace of job flows and wages in the economy.

4.3 Empirical Analysis

4.3.1 Firms Per Worker and Labor Market Flows

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 in the declining pace of job-to-job transitions, and transitions to and from employment. In this section, I provide descriptive evidence of the association between labor market flows and the firm to worker ratio. The reduced-form specification is the following:

$$log(LaborFlow)_{jmt} = \beta_0 + \beta_1 log(FirmsPerWorker)_{jmt} + \beta_2 X_{jmt} + \alpha_{jt} + \alpha_{mt} + \epsilon_{jmt} \quad (11)$$

where $log(LaborFlow)_{jmt}$ is the log of average transition rates, including job-to-job, non-employment to employment, and employment to non-employment, in sector j, MSA m, and in year t. The main explanatory variable $log(FirmsPerWorker)_{jmt}$ is the log of the firm to worker ratio; X_{jmt} 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 labor flows are identified from variation across local labor markets, denoted by metropolitan area-sector pairs, controlling for time-varying characteristics of sectors and metropolitan areas.[25] All standard errors are clustered at the metropolitan area-by-sector level.

Table (4a) columns (1)-(7) report the coefficient on log firms per worker from estimating different specifications of equation (11), where the dependent variable is the job-to-job transition rate. Overall, a higher number of firms per worker is associated with a significantly higher job-to-job transitions rate. When the specification is run without any fixed effects or with only the year fixed effects, a one log point increase in firms per worker is associated with an increase of about 0.15 log points in the job to job transition rate. Upon controlling for sector fixed effects (specification 3) the coefficient drops to 0.04 and the R^2 increases substantially, showing that a large part of the positive relations in specifications (1) and (2) was driven by variation across sectors. Further, allowing for MSA-fixed effects

[25] I do not use time-series variation 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.

(specification 4) reduces the coefficient to 0.02. The coefficient remains nearly stable in specification (5) when introducing MSA-year and sector-year fixed effects, showing that the effects are not driven by sector- or MSA-specific characteristics that have varied over time, but rather those characteristics that are fixed. Additionally, controlling for the composition of workers' age and education (specification 6) reduces the coefficient to about 0.015, indicating that worker demographics may be driving some of the effects. This is expected, as older workers tend to have a lower job to job transitions probability than younger workers. Compared to specification (4) and (5), the relation between firms per worker and job to job transitions remains stable when controlling for workforce composition across both worker and firm demographic groups (specification 7). Thus, specifications (4)-(7) suggest that controlling for location- and sector-specific shocks, job-to-job transition rates are higher in markets with more firms per worker. The elasticity of job to job transition rate to firms per worker varies between 0.015-0.026. As a robustness check, the final specification regresses log job to job transition counts on log firms and log employees and finds both coefficients to be positive and significant, with log firms being of higher magnitude.

Tables (4b) and (4c) presents results from estimating the same specifications of equation (11) as in Table (4a) but with dependent variables non-employment to employment hires rate, and employment to non-employment separations rate, respectively. Both tables show that comparing specifications (1)-(2) to (4)-(5), much of the variation in identifying the relation between firms per worker and hires or separations rate is explained by variation across MSAs and sectors over time. Further, unlike the case with job-to-job transitions, adding worker and firm fixed effects in specification (7) dramatically reduces the coefficient on log firms per worker and increases R^2, suggesting that worker composition across various demographic groups played an important role in driving the positive coefficients seen in the earlier specifications. Finally, column (8) shows that log firms and log workers are positively associated with log hires and separations counts, with the coefficient on firms being higher in magnitude. Overall, the coefficients are positive and significant across all specifications of Tables (4b) and(4c). The coefficients are larger for hires than separations. From an empirical standpoint, this could be because the hires rate is greater in magnitude and varies more than the separations rate. From the model's perspective, this could be because the number of firms is more relevant to the outside option of the nonemployed job seekers, and therefore affects the hires rate directly. The link to the separations rate is not a direct one and shut off in the model.

To sum, this section shows a positive association between firms per worker and labor market flows, and these results are robust when controlling for time-varying characteris-

Table 4: Regressions of Labor Market Transitions on Number of Firms per Worker

(a) OLS Regressions: Log (Job-to-Job Hires) on Log(Firms per Worker)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log Firms per Worker	0.146***	0.148***	0.0439***	0.0206***	0.0261***	0.0150**	0.0224***	
	(0.00579)	(0.00591)	(0.00626)	(0.00616)	(0.00640)	(0.00589)	(0.00770)	
Log Firms								0.551***
								(0.0173)
Log Workers								0.386***
								(0.0143)
Year FE		✓	✓	✓				
Sector FE			✓	✓				
MSA FE				✓				
MSA-Year FE					✓	✓	✓	✓
Sector-Year FE					✓	✓	✓	✓
Worker controls						✓	✓	✓
Firm controls							✓	✓
Observations	99979	99979	99979	99979	99979	97679	70584	72766
R^2	0.0496	0.113	0.622	0.723	0.766	0.806	0.861	0.962
R^2 adjusted	0.0496	0.113	0.622	0.722	0.748	0.791	0.846	0.958

(b) OLS Regressions: Log (Nonemployment-to-Employment Hires) on Log(Firms per Worker)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log Firms per Worker	0.227***	0.224***	0.195***	0.144***	0.149***	0.104***	0.0541***	
	(0.00820)	(0.00824)	(0.00767)	(0.00810)	(0.00850)	(0.00702)	(0.00855)	
Log Firms								0.540***
								(0.0184)
Log Workers								0.363***
								(0.0143)
Year FE		✓	✓	✓				
Sector FE			✓	✓				
MSA FE				✓				
MSA-Year FE					✓	✓	✓	✓
Sector-Year FE					✓	✓	✓	✓
Worker controls						✓	✓	✓
Firm controls							✓	✓
Observations	100279	100279	100279	100279	100279	97856	71839	72278
R^2	0.0657	0.0775	0.748	0.785	0.806	0.856	0.910	0.961
R^2 adjusted	0.0657	0.0773	0.748	0.784	0.791	0.844	0.900	0.957

Notes: This table displays regressions of labor market transitions on number of firms per worker. Sub-table (4a) regresses log of job-to-job hires rate on log firms per worker in columns (1)-(7), and log of job-to-job hires counts on log firms and log workers in column (8). Sub-table (4b) performs the same regressions with dependent variable log of non-employment to employment hires rate, and corresponding counts, respectively in columns (1)-(7) and column (8). Sectors are defined as two-digit NAICS industries. Worker controls include the fraction of workforce in each sector-MSA-year cell belonging to different age, and education groups. 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 4: Regressions of Labor Market Transitions on Number of Firms per Worker, continued

(c) OLS Regressions: Log (Employment-to-Nonemployment Separations) on Log(Firms per Worker)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log Firms per Worker	0.194***	0.192***	0.156***	0.106***	0.110***	0.0771***	0.0275***	
	(0.00644)	(0.00649)	(0.00602)	(0.00634)	(0.00663)	(0.00590)	(0.00739)	
Log Firms								0.526***
								(0.0176)
Log Workers								0.395***
								(0.0141)
Year FE		✓	✓	✓				
Sector FE			✓	✓				
MSA FE				✓				
MSA-Year FE					✓	✓	✓	✓
Sector-Year FE					✓	✓	✓	✓
Worker controls						✓	✓	✓
Firm controls							✓	✓
Observations	100353	100353	100353	100353	100353	97927	72238	72558
R^2	0.0730	0.101	0.729	0.770	0.796	0.836	0.895	0.963
R^2 adjusted	0.0730	0.101	0.729	0.769	0.780	0.823	0.883	0.958

Notes: This table displays regressions of labor market transitions on number of firms per worker. Sub-table (4c) regresses log of employment to non-employment separations rate on log firms per worker in columns (1)-(7), and log of employment to non-employment separations counts on log firms and log workers in column (8). Sectors are defined as two-digit NAICS industries. Worker controls include the fraction of workforce in each sector-MSA-year cell belonging to different age, and education groups. 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

tics 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 of declining labor market dynamism in the face of the declining number of firms.

4.3.2 Firms Per Worker and Average Wages

To estimate the relation between firms per worker and average wages of workers making labor market transitions, I run the following regression:

$$log(wages)_{jmt} = \beta_0 + \beta_1 log(FirmsPerWorker)_{jmt} + \beta_2 X_{jmt} + \alpha_{jm} + \alpha_{mt} + \alpha_{jt} + \epsilon_{jmt} \quad (12)$$

where $log(wage)_{jmt}$ is the log of the average real wage of workers making job-to-job, nonemployment to employment, and employment to nonemployment transitions in sector-j, MSA-m, and year-t. The main variable of interest $log(FirmsPerWorker)$ is as before, and control variables include workforce composition of a metropolitan area-sector-year cell in various firm-size and age groups.[26] α_{jm} is a vector of sector-by-MSA (market) level fixed effects, to control for fixed differences across markets. α_{jt} is a vector of time-varying sector effects to control for sector-specific shocks. Finally, 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 identifying variation in equation (12) stems from market-specific, time-varying differences in firms per worker. The key concern, as pointed in the literature, 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. This instrument captures the vari-

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

ation in firms per worker that is not driven by changes in a sector of any one 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 (12), 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 results of the various specifications of equation (12) below.

Table (5a) shows results from the baseline specification of average real wages of job-to-job hires regression on firms per workers. Specifications (1) and (2) introduce year and market effects, and show a negative coefficient on log firms per worker. On adding employment share across various firm age and size groups in specification (3), 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.[27] Specifications (4) and (5) allow for time-varying MSA and sector-effects. The coefficient on log firms per worker does not vary much compared to specification (3) when introducing MSA-year fixed effects, but drops in magnitude and become insignificant when sector-year fixed effects are also added. The latter could be a result of soaking up most of the variation in firms per worker as a result of adding a full set of controls. I, therefore, consider column (4) as the preferred specification.

Specifications (6)-(9) are instrumental variable counterparts of specifications (1)-(4). The signs of the coefficient are positive and significant for all specifications, and their magnitudes are higher compared to the OLS estimates. Introducing controls for firm demographic composition increases the magnitude of the coefficient in specification (8) compared to (6)-(7), while further adding MSA-year fixed effects (specification 9) does not affect the coefficient. Depending on the specification, a 10% increase in firms per worker is associated with a 0.5%-3.2% increase in average wages of job-to-job hires. Appendix table (A1a) presents results from the first stage.

Next, tables (5b) and (5c) show the effect of firms per worker on wages of hires from and separations to non-employment, respectively. The preferred specification in column (4) examines variation within markets, controlling for MSA-specific shocks, and finds a

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

Table 5: 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)	(7)	(8)	(9)
Log Firms per Worker	-0.0108**	-0.0223***	0.0111*	0.0262***	0.00139	0.0527***	0.144***	0.324***	0.320***
	(0.00547)	(0.00575)	(0.00644)	(0.00610)	(0.00566)	(0.00858)	(0.0241)	(0.0293)	(0.0270)
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Sector-MSA FE		✓	✓	✓	✓		✓	✓	✓
MSA-Year FE				✓	✓				✓
Sector-Year FE					✓				
Firm controls			✓	✓	✓			✓	✓
Observations	98283	98162	70277	70260	70253	92261	91944	67448	67431
R^2	0.00510	0.839	0.930	0.942	0.948	-0.00705	0.855	0.922	0.936
R^2 adjusted	0.00491	0.827	0.925	0.930	0.937	-0.00726	0.845	0.916	0.922

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

	OLS					IV			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log Firms per Worker	0.000916	-0.0225***	-0.0126*	0.00996	-0.0207***	0.101***	0.150***	0.377***	0.379***
	(0.00643)	(0.00586)	(0.00701)	(0.00695)	(0.00654)	(0.0105)	(0.0253)	(0.0362)	(0.0329)
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Sector-MSA FE		✓	✓	✓	✓		✓	✓	✓
MSA-Year FE				✓	✓				✓
Sector-Year FE					✓				
Firm controls			✓	✓	✓			✓	✓
Observations	99369	99251	69752	69736	69730	92952	92625	66907	66891
R^2	0.00147	0.860	0.909	0.924	0.930	-0.0148	0.865	0.899	0.917
R^2 adjusted	0.00127	0.851	0.902	0.909	0.915	-0.0150	0.856	0.891	0.899

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

	OLS					IV			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log Firms per Worker	-0.0491***	-0.0273***	0.00107	0.0181***	-0.0123*	0.0316***	0.130***	0.410***	0.408***
	(0.00626)	(0.00556)	(0.00695)	(0.00681)	(0.00633)	(0.00984)	(0.0236)	(0.0355)	(0.0337)
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Sector-MSA FE		✓	✓	✓	✓		✓	✓	✓
MSA-Year FE				✓	✓				✓
Sector-Year FE					✓				
Firm controls			✓	✓	✓			✓	✓
Observations	99970	99837	69666	69649	69642	93784	93488	66836	66819
R^2	0.00851	0.869	0.910	0.923	0.929	-0.00472	0.866	0.898	0.914
R^2 adjusted	0.00832	0.860	0.903	0.908	0.914	-0.00492	0.857	0.891	0.896

Notes: This table displays OLS and instrumental variable regressions of wages associated with labor market transitions on number of firms per worker. Columns (1)-(5) of sub-tables (5a)-(5c) respectively, shows the OLS regression of log of wages associated with job to job hires, nonemployment-to-employment hires, and employment-to-nonemployment 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

positive coefficient for hires and separations. Instrumenting for the number of firms per worker, and running the same specification in column (9) yields positive coefficients that are larger in magnitude than the OLS counterparts, much like the results in table (5a). A 10% increase in firms per worker is associated with a 1.0%-3.8% increase in wages of hires from non-employment, and a 0.3%-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 vacancies 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 workers and 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. Second, I raise the bargaining power of workers in the wage negotiation protocol. Across both these counterfactual exercises, I document an increase in job flows and average wages as firm market power decreases and worker market power increases.

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, in line with the predictions of the model, I document a positive correlation between firms per worker, labor market transitions, and average wages.

I 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 a high-level 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. I leave that as an area of future research for this project. Nevertheless, this paper takes a first step in understanding the link between two widely discussed and contended macroeconomic aggregates in the US economy - rising firm market power and declining labor market dynamism - and explores its implications on wages.

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A Model Appendix

A.1 Nash Bargaining

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

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

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).

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

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 Deriving Surplus Function

Defining the Nash bargaining equation in terms of surplus:

$$\begin{aligned}
W(\theta_i, \theta_j) &= \widetilde{W}(\theta_j, \theta_j, \theta_i) + \alpha(W(\theta_i, \theta_i) - \widetilde{W}(\theta_j, \theta_j, \theta_i)) \\
W(\theta_i, \theta_j) - U_i &= (1-\alpha)(\widetilde{W}(\theta_j, \theta_j, \theta_i) - U_j) + \alpha(W(\theta_i, \theta_i) - U_i) + (1-\alpha)(U_j - U_i) \\
&= (1-\alpha)\widetilde{S}(\theta_j, \theta_i) + \alpha S(\theta_i) + (1-\alpha)(U_j - U_i)
\end{aligned}$$

Rewriting equation for $\widetilde{W}$ and subtracting $U(\theta_i) \equiv U_i$:

$$\begin{aligned}
\widetilde{W}(\theta_i, \theta_i, \theta_h) - U_i = \theta_i - (1-\beta)U_i + \beta\Bigg\{ & \delta(U - U_i) + (1-\delta)\Bigg[\lambda_1 \sum_{x=i}^{N} \Big(W(\theta_x, \theta_i) - U_i\Big) n_x f(\theta_x) \\
& - \lambda_1 \Big(W(\theta_h, \theta_i) - U_i\Big) f(\theta_h) - \lambda_1 \Big(W(\theta_i, \theta_i) - U_i\Big) f(\theta_i) \\
& + \Bigg(1 - \lambda_1 \sum_{x=i}^{N} n_x f(\theta_x) + \lambda_1 f(\theta_h) + \lambda_1 f(\theta_i)\Bigg)\Big(\widetilde{W}(\theta_i, \theta_i, \theta_h) - U_i\Big)\Bigg]\Bigg\} \\
\widetilde{S}(\theta_i, \theta_h) = \theta_i - (1-\beta)U_i + \beta\Bigg\{ & \delta(U - U_i) \\
& + (1-\delta)\Bigg[\lambda_1 \sum_{x=i}^{N} \Big((1-\alpha)\widetilde{S}(\theta_i, \theta_x) + \alpha S(\theta_x) + \alpha(U_x - U_i)\Big) n_x f(\theta_x) \\
& - \lambda_1 \Big((1-\alpha)\widetilde{S}(\theta_i, \theta_h) + \alpha S(\theta_h) + \alpha(U_h - U_i)\Big) f(\theta_h) \\
& - \lambda_1 S(\theta_i) f(\theta_i) + \Bigg(1 - \lambda_1 \sum_{x=i}^{N} n_x f(\theta_x) + \lambda_1 f(\theta_h) + \lambda_1 f(\theta_i)\Bigg)\widetilde{S}(\theta_i, \theta_h)\Bigg]\Bigg\} \\
\widetilde{S}(\theta_i, \theta_h) = \theta_i - (1-\beta)U_i + \beta\Bigg\{ & \delta(U - U_i) \\
& + (1-\delta)\Bigg[\lambda_1 \sum_{x=i+1}^{N} \Big((1-\alpha)\widetilde{S}(\theta_i, \theta_x) + \alpha S(\theta_x) + \alpha(U_x - U_i)\Big) n_x f(\theta_x) \\
& - \lambda_1 \Big((1-\alpha)\widetilde{S}(\theta_i, \theta_h) + \alpha S(\theta_h) + \alpha(U_h - U_i)\Big) f(\theta_h) \\
& + \lambda_1 S(\theta_i) f(\theta_i)(n_i - 1) \\
& + \Bigg(1 - \lambda_1 \sum_{x=i+1}^{N} n_x f(\theta_x) + \lambda_1 f(\theta_h) - \lambda_1 f(\theta_i)(n_i - 1)\Bigg)\widetilde{S}(\theta_i, \theta_h)\Bigg]\Bigg\}
\end{aligned}$$

Then for $h = i$, $\widetilde{S}(\theta_i, \theta_i) = S(\theta_i)$ we can write the above expression as:

$$\begin{aligned} S(\theta_i) = \theta_i - (1-\beta)U_i + \beta\Bigg\{ & \delta(U - U_i) \\ & + (1-\delta)\Bigg[\lambda_1\Bigg(\sum_{x=i+1}^{N}\Big((1-\alpha)\widetilde{S}(\theta_i,\theta_x) + \alpha S(\theta_x) + \alpha(U_x - U_i)\Big)n_x f(\theta_x)\Bigg) \\ & + \Bigg(1 - \lambda_1\Bigg(\sum_{x=i+1}^{N} n_x f(\theta_x)\Bigg)S(\theta_i)\Bigg]\Bigg\} \end{aligned}$$

Thus, the system of equations can be represented by $\widetilde{S}(\theta_i, \theta_h), \forall h \geq i$, where when $h = i, \widetilde{S}(\theta_i, \theta_i) = S(\theta_i)$. Note the equation has another unknown θ_u, that is determined by $S(\theta_u) = \widetilde{S}(\theta_u, \theta_u) = 0$. Next, deriving expressions for unemployment:

$$\begin{aligned} U_i = z + \beta\Bigg\{ & \lambda_0\Bigg[\sum_{x=u}^{N} W(\theta_x,\theta_u)n_x f(\theta_x) - W(\theta_i,\theta_u)f(\theta_i) - W(\theta_u,\theta_u)f(\theta_u)\Bigg] \\ & + \Bigg(1 - \lambda_0\Bigg[\sum_{x=u}^{N} n_x f(\theta_x) - f(\theta_i) - f(\theta_u)\Bigg]\Bigg)U_i\Bigg\} \end{aligned}$$

$$\begin{aligned} U_i\Bigg[1 - \beta\Bigg(1 - \lambda_0\sum_{x=u}^{N} n_x f(\theta_x)\Bigg)\Bigg] &= z + \beta\Bigg\{\lambda_0\Bigg[\sum_{x=u}^{N} W(\theta_x,\theta_u)n_x f(\theta_x) - \Big(W(\theta_i,\theta_u) - U_i\Big)f(\theta_i) \\ &\quad - \Big(W(\theta_u,\theta_u) - U_i\Big)f(\theta_u)\Bigg]\Bigg\} \\ &= z + \beta\Bigg\{\lambda_0\Bigg[\sum_{x=u}^{N} W(\theta_x,\theta_u)n_x f(\theta_x) \\ &\quad - \Big((1-\alpha)\widetilde{S}(\theta_u,\theta_i) + \alpha S(\theta_i) + (1-\alpha)(U_u - U_i)\Big)f(\theta_i) \\ &\quad - \Big(W(\theta_u,\theta_u) - U_i\Big)f(\theta_u)\Bigg]\Bigg\} \end{aligned}$$

By assumption $W(\theta_u, \theta_u) = U_u$ we have,

$$\begin{aligned} U_i\Bigg[1 - \beta\Bigg(1 - \lambda_0\sum_{x=u}^{N} n_x f(\theta_x)\Bigg)\Bigg] = z + \beta\Bigg\{ & \lambda_0\Bigg[\sum_{x=u}^{N} W(\theta_x,\theta_u)n_x f(\theta_x) \\ & - \Big((1-\alpha)\widetilde{S}(\theta_u,\theta_i) + \alpha S(\theta_i)\Big)f(\theta_i) \\ & - (U_u - U_i)\Big((1-\alpha)f(\theta_i) + f(\theta_u)\Big)\Bigg]\Bigg\} \end{aligned}$$

Then deriving expression for $U_u - U_i$:

$$U_u\Bigg(1-\beta\Bigg(1-\lambda_0\sum_{x=u}^{N} n_x f(\theta_x)\Bigg)\Bigg) = z+\beta\Bigg\{\lambda_0\sum_{x=u}^{N} W(\theta_x,\theta_u)n_x f(\theta_x)\Bigg\}$$

$$(U_u-U_i)\Bigg(1-\beta\Bigg(1-\lambda_0\sum_{x=u}^{N} n_x f(\theta_x)\Bigg)\Bigg) = \beta\lambda_0\Bigg[\Bigg((1-\alpha)\widetilde{S}(\theta_u,\theta_i)+\alpha S(\theta_i)\Bigg)f(\theta_i) + (U_u-U_i)\Bigg((1-\alpha)f(\theta_i)+f(\theta_u)\Bigg)\Bigg]$$

$$U_u - U_i = \frac{\beta\lambda_0\Bigg((1-\alpha)\widetilde{S}(\theta_u,\theta_i)+\alpha S(\theta_i)\Bigg)f(\theta_i)}{1-\beta+\beta\lambda_0\Bigg[\sum\limits_{x=u}^{N} n_x f(\theta_x)-(1-\alpha)f(\theta_i)-f(\theta_u)\Bigg]}$$

Thus,

$$U_i - U_j = \beta\lambda_0\cdot\Bigg\{\frac{\Bigg((1-\alpha)\widetilde{S}(\theta_u,\theta_j)+\alpha S(\theta_j)\Bigg)f(\theta_j)}{1-\beta+\beta\lambda_0\Bigg[f^1-(1-\alpha)f(\theta_j)-f(\theta_u)\Bigg]} - \frac{\Bigg((1-\alpha)\widetilde{S}(\theta_u,\theta_i)+\alpha S(\theta_i)\Bigg)f(\theta_i)}{1-\beta+\beta\lambda_0\Bigg[f^1-(1-\alpha)f(\theta_i)-f(\theta_u)\Bigg]}\Bigg\}$$

Finally, deriving expression for $U_i(1-\beta)$, for ease of notation I write: $S_{ux} = (1-\alpha)\widetilde{S}(\theta_u,\theta_x)+\alpha S(\theta_x)$.

$$U_i = z+\beta\Bigg\{\lambda_0\Bigg[\sum_{x=u}^{N} W(\theta_x,\theta_u)n_x f(\theta_x) - W(\theta_i,\theta_u)f(\theta_i) - W(\theta_u,\theta_u)f(\theta_u)\Bigg] + \Bigg(1-\lambda_0\Bigg[\sum_{x=u}^{N} n_x f(\theta_x) - f(\theta_i) - f(\theta_u)\Bigg]\Bigg)U_i\Bigg\}$$

$$U_i(1-\beta) = z+\beta\lambda_0\Bigg[\sum_{x=u}^{N}(W(\theta_x,\theta_u)-U_x+U_x-U_i)n_x f(\theta_x) - (W(\theta_i,\theta_u)-U_i)f(\theta_i) - (W(\theta_u,\theta_u)-U_i)f(\theta_u)\Bigg]$$

$$U_i(1-\beta) = z + \beta\lambda_0\Bigg[\sum_{x=u}^{N}\Bigg((1-\alpha)\widetilde{S}(\theta_u,\theta_x) + \alpha S(\theta_x) + (1-\alpha)(U_u - U_x) + (U_x - U_i)\Bigg)n_x f(\theta_x)$$
$$- \Bigg((1-\alpha)\widetilde{S}(\theta_u,\theta_i) + \alpha S(\theta_i) + (1-\alpha)(U_u - U_i)\Bigg)f(\theta_i) - (U_u - U_i)f(\theta_u)\Bigg]$$

$$U_i(1-\beta) = z + \beta\lambda_0\Bigg[\sum_{x=u}^{N}\Bigg(S_{ux} + (U_u - U_i) - \alpha(U_u - U_x)\Bigg)n_x f(\theta_x) - S_{ui}f(\theta_i)$$
$$- (U_u - U_i)\Bigg((1-\alpha)f(\theta_i) + f(\theta_u)\Bigg)\Bigg]$$

Substituting for the unemployment expressions derived above:

$$U_i(1-\beta) = z + \beta\lambda_0\Bigg[\sum_{x=u}^{N}\Bigg(S_{ux} + \frac{\beta\lambda_0 S_{ui}f(\theta_i)}{1-\beta+\beta\lambda_0\Bigg[\sum\limits_{x=u}^{N} n_x f(\theta_x) - (1-\alpha)f(\theta_i) - f(\theta_u)\Bigg]}$$
$$- \frac{\alpha\beta\lambda_0 S_{ux}f(\theta_x)}{1-\beta+\beta\lambda_0\Bigg[\sum\limits_{x=u}^{N} n_x f(\theta_x) - (1-\alpha)f(\theta_x) - f(\theta_u)\Bigg]}\Bigg)n_x f(\theta_x)$$
$$- S_{ui}f(\theta_i) - (U_u - U_i)\Bigg((1-\alpha)f(\theta_i) + f(\theta_u)\Bigg)\Bigg]$$

$$U_i(1-\beta) = z + \beta\lambda_0\Bigg[\sum_{x=u}^{N}\Bigg(S_{ux}\Bigg(\frac{1-\beta+\beta\lambda_0\Bigg[\sum\limits_{x=u}^{N} n_x f(\theta_x) - f(\theta_x) - f(\theta_u)\Bigg]}{1-\beta+\beta\lambda_0\Bigg[\sum\limits_{x=u}^{N} n_x f(\theta_x) - (1-\alpha)f(\theta_x) - f(\theta_u)\Bigg]}\Bigg)$$
$$+ \frac{\beta\lambda_0 S_{ui}f(\theta_i)}{1-\beta+\beta\lambda_0\Bigg[\sum\limits_{x=u}^{N} n_x f(\theta_x) - (1-\alpha)f(\theta_i) - f(\theta_u)\Bigg]}\Bigg)n_x f(\theta_x)$$
$$- S_{ui}f(\theta_i)\Bigg(\frac{1-\beta+\beta\lambda_0\Bigg[\sum\limits_{x=u}^{N} n_x f(\theta_x)\Bigg]}{1-\beta+\beta\lambda_0\Bigg[\sum\limits_{x=u}^{N} n_x f(\theta_x) - (1-\alpha)f(\theta_i) - f(\theta_u)\Bigg]}\Bigg)\Bigg]$$

The final model can be expressed as the following value functions:

$$\widetilde{S}(\theta_i,\theta_h) = \theta_i - (1-\beta)U_i + \beta\Bigg\{\delta(U - U_i)$$
$$+ (1-\delta)\Bigg[\lambda_1\sum_{x=i+1}^{N}\Bigg((1-\alpha)\widetilde{S}(\theta_i,\theta_x) + \alpha S(\theta_x) + \alpha(U_x - U_i)\Bigg)n_x f(\theta_x)$$
$$- \lambda_1\Bigg((1-\alpha)\widetilde{S}(\theta_i,\theta_h) + \alpha S(\theta_h) + \alpha(U_h - U_i)\Bigg)f(\theta_h)$$

$$+\lambda_1 S(\theta_i)(n_i-1)f(\theta_i)$$
$$+\left(1-\lambda_1\sum_{x=i+1}^{N}n_x f(\theta_x)+\lambda_1 f(\theta_h)-\lambda_1(n_i-1)f(\theta_i)\right)\widetilde{S}(\theta_i,\theta_h)\Bigg]\Bigg\},\forall h\geq i$$
$$\widetilde{S}(\theta_u,\theta_u)=0$$

where $S(\theta_i)=\widetilde{S}(\theta_i,\theta_i),\forall i$, and:

$$U_i(1-\beta)=z+\beta\lambda_0\sum_{x=u}^{N}\Bigg(\frac{S_{ux}\cdot\left(1-\beta+\beta\lambda_0\left[f^1-f(\theta_u)-f(\theta_x)\right]\right)}{1-\beta+\beta\lambda_0\left[f^1-(1-\alpha)f(\theta_x)-f(\theta_u)\right]}$$
$$+\frac{\beta\lambda_0 S_{ui}f(\theta_i)}{1-\beta+\beta\lambda_0\left[f^1-(1-\alpha)f(\theta_i)-f(\theta_u)\right]}\Bigg)n_x f(\theta_x)$$
$$-\frac{\beta\lambda_0 S_{ui}f(\theta_i)(1-\beta+\beta\lambda_0 f^1)}{1-\beta+\beta\lambda_0\left[f^1-(1-\alpha)f(\theta_i)-f(\theta_u)\right]}$$
$$U_u-U_i=\frac{\beta\lambda_0\left((1-\alpha)\widetilde{S}(\theta_u,\theta_i)+\alpha S(\theta_i)\right)f(\theta_i)}{1-\beta+\beta\lambda_0\left[\sum_{x=u}^{N}n_x f(\theta_x)-(1-\alpha)f(\theta_i)-f(\theta_u)\right]}=U-U_i$$
$$U_i-U_j=\beta\lambda_0\cdot\Bigg\{\frac{\left((1-\alpha)\widetilde{S}(\theta_u,\theta_j)+\alpha S(\theta_j)\right)f(\theta_j)}{1-\beta+\beta\lambda_0\left[f^1-(1-\alpha)f(\theta_j)-f(\theta_u)\right]}$$
$$-\frac{\left((1-\alpha)\widetilde{S}(\theta_u,\theta_i)+\alpha S(\theta_i)\right)f(\theta_i)}{1-\beta+\beta\lambda_0\left[f^1-(1-\alpha)f(\theta_i)-f(\theta_u)\right]}\Bigg\}$$

A.3 Solution Algorithm

The solution algorithm involves decoupling the system of equations of the weak upper triangular matrix $\widetilde{S}(\theta_i,\theta_j),\forall i\leq j$ into the diagonal matrix $S(\theta_i)\equiv\widetilde{S}(\theta_i,\theta_i)$ and the strict upper triangular matrix $\widetilde{S}(\theta_i,\theta_j),\forall j>i$. This is done because the constraint is only on the diagonal elements and not on the rest of the matrix. I write the following algorithm to solve the model numerically:

While $\widetilde{S}'\neq\widetilde{S}$ & $S'\neq S$:

- Solve for $S(\theta_i) \equiv \widetilde{S}(\theta_i, \theta_i)$, as a function of $\widetilde{S}, \theta, f$.
- Find θ_u satisfying $S(\theta_u) = 0$.
- Update θ and $f(\theta)$ grid and interpolate/extrapolate $S(\theta_i)$ to the updated grid. Call this S'.
- Solve for $\widetilde{S}'(\theta_i, \theta_j)$ for all $j > i$, as a function of S', θ', f'. Note, for $j = i$, $\widetilde{S}' = S'$.
- Compute error and update: $\widetilde{S} = \widetilde{S}'$ and $S = S'$.

A.4 Wage Function

Start with the worker value function:

$$\begin{aligned}
W(\theta_i, \theta_j) &= \omega(\theta_i, \theta_j) + \beta\Bigg[\delta U + (1-\delta)\Bigg(\lambda_1 \sum_{x=i+1}^{N} W(\theta_x, \theta_i) f(\theta_x) \\
&\qquad + \lambda_1 \sum_{x=j+1}^{i} W(\theta_i, \theta_x) f(\theta_x) + \Bigg(1 - \lambda_1 \sum_{x=j+1}^{N} f(\theta_x)\Bigg) W(\theta_i, \theta_j)\Bigg)\Bigg] \\
W(\theta_i, \theta_j) - U_i &= \omega(\theta_i, \theta_j) - U_i(1-\beta) + \beta\Bigg[\delta(U - U_i) \\
&\qquad + (1-\delta)\Bigg(\lambda_1 \sum_{x=i+1}^{N} (W(\theta_x, \theta_i) - U_x + U_x - U_i) f(\theta_x) + \\
&\qquad \lambda_1 \sum_{x=j+1}^{i} (W(\theta_i, \theta_x) - U_i) f(\theta_x) + \Bigg(1 - \lambda_1 \sum_{x=j+1}^{N} f(\theta_x)\Bigg)(W(\theta_i, \theta_j) - U_i)\Bigg)\Bigg]
\end{aligned}$$

Then using $W(\theta_i, \theta_j) - U_i = (1-\alpha)\widetilde{S}(\theta_j, \theta_i) + \alpha S(\theta_i) + (1-\alpha)(U_j - U_i)$ and rewriting expressions:

$$\begin{aligned}
W(\theta_i, \theta_x) - U_i &= (1-\alpha)\widetilde{S}(\theta_j, \theta_i) + \alpha S(\theta_i) + (1-\alpha)(U_j - U_i) \\
&\qquad + (1-\alpha)\Bigg(\widetilde{S}(\theta_x, \theta_i) - \widetilde{S}(\theta_j, \theta_i)\Bigg) + (1-\alpha)\Bigg((U_x - U_j)\Bigg) \\
W(\theta_x, \theta_i) - U_x &= (1-\alpha)\widetilde{S}(\theta_j, \theta_i) + \alpha S(\theta_i) + (1-\alpha)(U_j - U_i) \\
&\qquad + (1-\alpha)(\widetilde{S}(\theta_i, \theta_x) - \widetilde{S}(\theta_j, \theta_i)) + \alpha(S(\theta_x) - S(\theta_i)) + (1-\alpha)(U_i - U_x - U_j + U_i)
\end{aligned}$$

Substituting in the worker value function:

$$(W(\theta_i, \theta_j) - U_i)(1 - \beta(1-\delta)) = \omega(\theta_i, \theta_j) - U_i(1-\beta) + \beta\Bigg[\delta(U - U_i)$$

$$
\begin{aligned}
&+ (1-\delta)\lambda_1 \Bigg(\sum_{x=i+1}^{N} ((1-\alpha)(\widetilde{S}(\theta_i,\theta_x) - \widetilde{S}(\theta_j,\theta_i)) \\
&+ \alpha(S(\theta_x) - S(\theta_i)) + (1-\alpha)(U_i - U_j) + \alpha(U_x - U_i))f(\theta_x) \\
&+ \sum_{x=j+1}^{i} ((1-\alpha)\Bigg(\widetilde{S}(\theta_x,\theta_i) - \widetilde{S}(\theta_j,\theta_i)\Bigg) + (1-\alpha)\Bigg((U_x - U_j)\Bigg))f(\theta_x)\Bigg)\Bigg]
\end{aligned}
$$

Define G to simplify the expression above:

$$
\begin{aligned}
G(\theta_i,\theta_j) = \Bigg\{ &\sum_{x=i+1}^{N} \Bigg((1-\alpha)(\widetilde{S}(\theta_i,\theta_x) - \widetilde{S}(\theta_j,\theta_i)) \\
&+ \alpha(S(\theta_x) - S(\theta_i)) + (1-\alpha)(U_i - U_j) + \alpha(U_x - U_i)\Bigg) f(\theta_x) \\
&+ \sum_{x=j+1}^{i} \Bigg((1-\alpha)\Bigg(\widetilde{S}(\theta_x,\theta_i) - \widetilde{S}(\theta_j,\theta_i)\Bigg) + (1-\alpha)(U_x - U_j)\Bigg) f(\theta_x)\Bigg\}
\end{aligned}
$$

which gives the expression for wage:

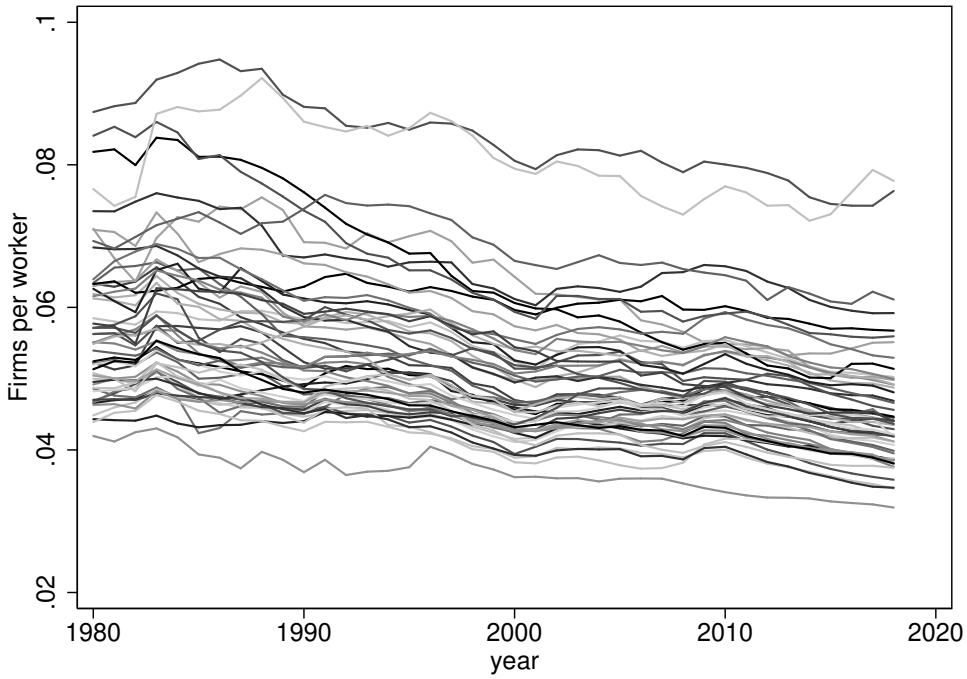
$$
\begin{aligned}
\omega(\theta_i,\theta_j) = &\Bigg((1-\alpha)\widetilde{S}(\theta_j,\theta_i) + \alpha S(\theta_i) + (1-\alpha)(U_j - U_i)\Bigg)(1-\beta(1-\delta)) \\
&+ U_i(1-\beta) - \beta\Bigg[\delta(U - U_i) + (1-\delta)\lambda_1 G(\theta_i,\theta_j)\Bigg]
\end{aligned}
$$

or more simply:

$$
\begin{aligned}
\omega(\theta_i,\theta_j) = W(\theta_i,\theta_j) - \beta\Bigg[&\delta U + (1-\delta)\Bigg(\lambda_1 \sum_{x=i+1}^{N} W(\theta_x,\theta_i) f(\theta_x) \\
&+ \lambda_1 \sum_{x=j+1}^{i} W(\theta_i,\theta_x) f(\theta_x) + \Bigg(1 - \lambda_1 \sum_{x=j+1}^{N} f(\theta_x)\Bigg) W(\theta_i,\theta_j)\Bigg)\Bigg]
\end{aligned}
$$

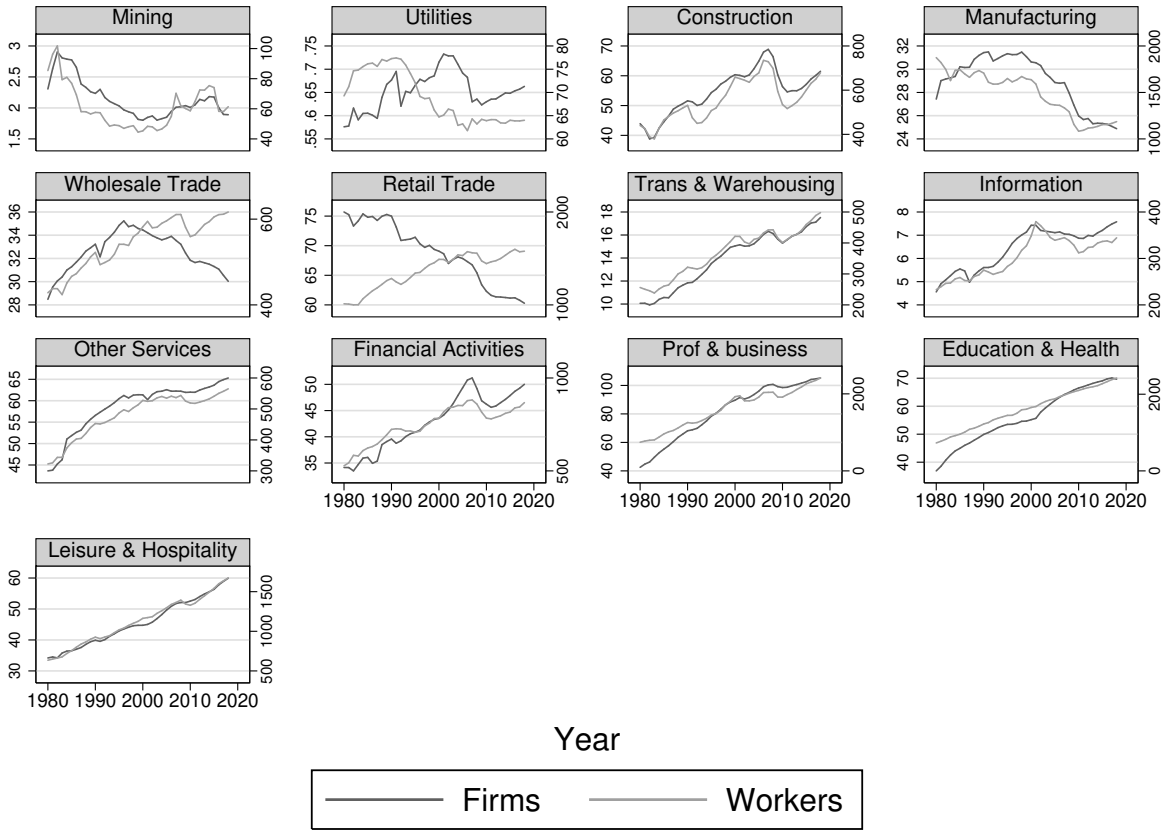
B Appendix Tables & Figures

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



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

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



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

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)	(4)
Avg Log Firms Per Workers in other MSAs	0.897***	0.864***	0.710***	0.718***
	(0.00869)	(0.0300)	(0.0267)	(0.0266)
Year FE	✓	✓	✓	✓
Sector-MSA FE		✓	✓	✓
MSA-Year FE				✓
Firm controls			✓	✓
Observations	92261	91944	67448	67431
R^2	0.573	0.940	0.968	0.972
R^2 adjusted	0.573	0.936	0.966	0.967
F	10669.5	829.3	192.1	182.1

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

	(1)	(2)	(3)	(4)
Avg Log Firms Per Workers in other MSAs	0.887***	0.868***	0.702***	0.711***
	(0.00887)	(0.0299)	(0.0262)	(0.0263)
Year FE	✓	✓	✓	✓
Sector-MSA FE		✓	✓	✓
MSA-Year FE				✓
Firm controls			✓	✓
Observations	92952	92625	66907	66891
R^2	0.562	0.936	0.968	0.972
R^2 adjusted	0.562	0.931	0.966	0.967
F	10001.4	844.9	195.0	182.5

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

	(1)	(2)	(3)	(4)
Avg Log Firms Per Workers in other MSAs	0.879***	0.849***	0.688***	0.697***
	(0.00902)	(0.0305)	(0.0267)	(0.0266)
Year FE	✓	✓	✓	✓
Sector-MSA FE		✓	✓	✓
MSA-Year FE				✓
Firm controls			✓	✓
Observations	93784	93488	66836	66819
R^2	0.550	0.933	0.968	0.972
R^2 adjusted	0.550	0.929	0.965	0.966
F	9480.8	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. 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$