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

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May 11, 2023

Abstract

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

JEL Classification: E2, J3, J6, J42

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

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

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1 Introduction

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

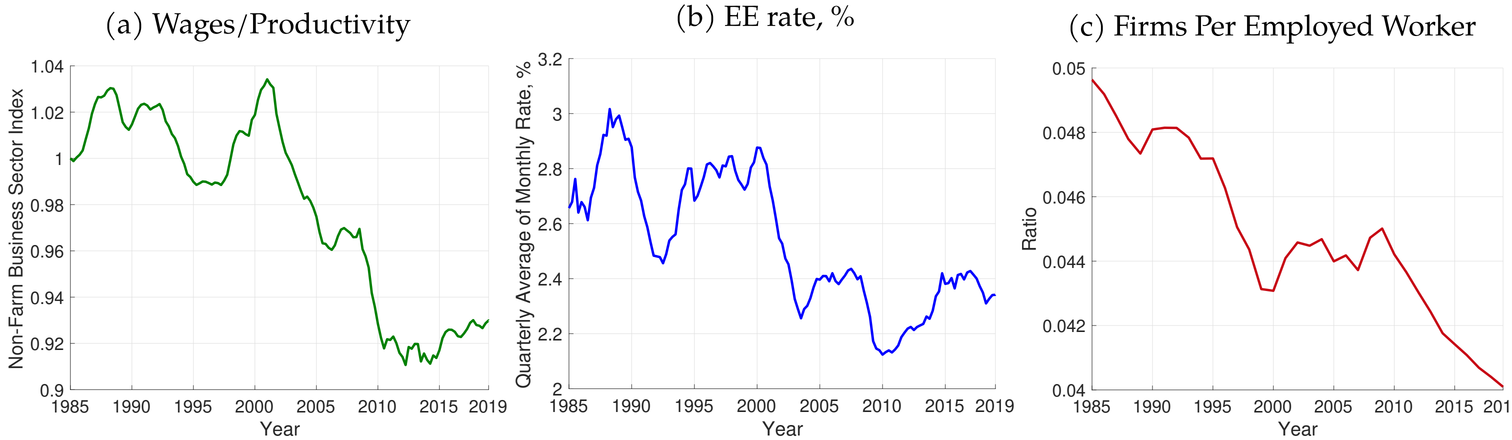
The theoretical predictions of the model can be seen in light of a recent empirical finding that aggregate real wages of the US economy covary much more strongly with the job-finding rate of the *employed*, rather than the *unemployed*, both of which act as a channel for transmission of labor demand (Moscarini & Postel-Vinay 2017, Karahan, Michaels, Pugsley, Şahin & Schuh 2017). The job-finding rate of the employed, which manifests in the pace of job-to-job transitions, reflects how intensely firms compete for employed workers. In this setting, the rising market power of firms translates to less competition among employers. Evidence of this has been documented in the form of lower outside offers for workers in more concentrated labor markets (Caldwell & Danieli 2022, Schubert, Stansbury & Taska 2022) and increasing instances of anti-competitive practices, such as non-compete covenants and no-poaching agreements, being enforced by firms (Krueger & Ashenfelter 2018, Starr, Bishara & Prescott 2020, Gottfries & Jarosch 2023). Both forces can potentially restrict the scope of labor reallocation to more productive, higher-paying jobs over the job ladder, thereby reducing average wages in the economy. This raises the question: to what extent can existing models of the labor market, with on-the-job

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

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

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

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



Notes: Bureau of Labor Statistics, Current Population Survey, and Business Dynamics Statistics, 1985-2019. Firms per worker are the ratio of annual stocks of the number of firms and employees. Post-1995 Employer-to-employer transitions rates are quarterly averages of monthly flows from Fujita, Moscarini & Postel-Vinay (2022) who use the Current Population Survey and correct for missing observations after a survey methodology change in 2007. Pre-1995 Employer-to-employer transitions rates are quarterly flows expressed as monthly rates (Diamond & Şahin 2016). Wages are expressed as a quarterly index of hourly compensation deflated by the implicit price deflator. Labor productivity is a quarterly index of output per hour deflated by the implicit price deflator. Wages and productivity are measured for the non-farm business sector. Figures (a) and (b) plot 4-quarter moving averages.

search linking job-to-job flows to average wages in equilibrium, quantitatively explain the aggregate decline in the two outcomes resulting from decreasing competition among firms for workers?

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

The pace at which workers climb the job ladder and match with more productive firms is a function of search frictions and firm competition in the labor market. The latter is governed by two ingredients: First, the model assumes a finite set of firms instead of a continuum of atomistic firms. This results in a discrete job offer distribution, with each firm having a non-zero vacancy share. Thus, decreasing the total number of firms in the economy increases any given firm's vacancy share, thereby granting them more weight in the offer distribution of job seekers. Second, employers exclude their offers from the outside options of their employees, similar in spirit to Jarosch, Nimczik & Sorkin (2023). In other words, when an employed worker contacts an outside firm, she prompts the incumbent and poaching employers to compete for her. This results in the worker and the potentially winning employer negotiating a wage that is a function of the foregone offer made by the losing employer, or in other words, the worker's outside option. A high offer made by the losing firm gives the worker more leverage in the bargain and forces the winning firm to match the higher value. However, the forgone outside offer contains the value from the option of searching on-the-job and matching with the firm that wins the worker. This means the winning firm competes with its own future offer in the continuation value of the worker's outside option. Removing such an offer reduces the outside option of the worker, consequently putting downward pressure on the negotiated wage and giving the winning firm more leverage in the bargain.

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

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

I evaluate the model against the 2012-17 US labor market by simulating a decrease in the number of firms per worker in the model. I find that the model can account for about 2/3rd of the decline in job-to-job transitions and about 18 percent of the decrease in wages as a fraction of productivity between the 1985 and 2017.

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

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

In line with the predictions of the model, four findings are noteworthy. First, I document a positive correlation between the number of firms per worker and EE transitions rate across local labor markets defined as Metropolitan Statistical Area (MSA)-sector pairs, using a rich set of fixed effects and controlling for workforce composition by the worker and firm demographic groups. Second, I document a positive relationship between the number of firms per worker and the payroll share of value-added, which proxies wages as a share of productivity across disaggregated industries. Third, the number of firms per worker correlates negatively with wage growth associated with job switches and positively with the wage growth of job stayers, controlling for individual and job-specific characteristics. Overall, the empirical evidence on EE transitions rate, wage growth, and average wage levels is consistent with the model's predictions.

Related literature. My theoretical and empirical findings contribute to the large literature exploring the role of employer market power on labor market outcomes. Two studies are closely related to the model presented in this paper. First, Jarosch, Nimczik &

Sorkin (2023) consider finite firms in a standard Diamond-Mortensen-Pissarides model where firms can remove their vacancies from the worker's outside options from the state of unemployment. The second, Schubert, Stansbury & Taska (2022), presents a framework with finite firms in which outside options of workers are a function of market concentration. Both studies predict that wages are inversely related to market concentration. The model presented in this paper differs from these studies by allowing firms to remove their vacancies from the worker's outside options from the state of unemployment *and* employment. The model further introduces wage bargaining in the tradition of Cahuc, Postel-Vinay & Robin (2006), between the poaching firm, incumbent firm and the worker who engages in on-the-job search. This allows the model to offer a novel market-power-based explanation for the falling EE transitions rate, apart from falling wages, which has been the focus of much of the current literature.[4][5]

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

The empirical strand of this literature documents the trends in employer market power in the aggregate and local labor markets and estimates its effects on average wages.

[4] Contemporaneous work by Berger, Herkenhoff, Kostol & Mongey (2023) studies the effect of employment-based Herfindahl Hirschman Indices (HHIs) on job flows, wages, and wage inequality in Norway. They find a negative correlation between HHIs and job flows and wages, in line with the results presented in this paper.

[5] On-the-job search among employed workers is motivated by recent work by Faberman, Mueller, Şahin & Topa (2022) who show not only that on-the-job search is ubiquitous but also that employed workers receive more solicited and unsolicited employer contacts than unemployed workers.

Yeh, Macaluso & Hershbein (2022) measure employer market power through plant level wage markdowns and find evidence of its consistent rise from the early 2000s. Brooks, Kaboski, Li & Qian (2021) use plant-level data for the manufacturing sectors of India and China and find evidence of monopsony power and its wage-suppressing effect. Other studies compute concentration measures such as employment share of the largest firms in an industry, as well as Herfindahl Hirschman indices in employment (Autor, Dorn, Katz, Patterson & Van Reenen 2020, Benmelech, Bergman & Kim 2020, Rinz 2020), hires (Marinescu, Ouss & Pape 2020), and vacancies (Azar, Marinescu, Steinbaum & Taska 2020, Azar, Marinescu & Steinbaum 2020). These studies document a negative correlation between the relevant measure of market concentration and average wages. Finally, two recent and related studies also document the relation between firm market power and workers' outside options. First, Caldwell & Danieli (2022) measure the cross-sectional competition faced by a worker from other similar workers across jobs to arrive at the worker's relevant outside options. They find a positive correlation between outside options of German workers and their wages. Second, Schubert, Stansbury & Taska (2022) compute a measure of outside options by examining the availability of local jobs outside a worker's occupation. They document a positive and significant effect of an increase in the value of job options outside a worker's occupation on wages.

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

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

2 Model

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

2.1 Agents

The continuous-time economy is populated by a unit continuum of homogeneous and infinitely lived workers. Each worker has linear preferences over the single good in the economy. Workers can either be employed or unemployed. Unemployed individuals derive utility from leisure, while employed workers provide a unit of labor to firms and receive a wage, denoted as ω.[6]

There exists a finite number of firms in the economy that are ex-ante heterogeneous in productivity. The total number of productivity levels is fixed to N, and firm productivity is denoted by $\theta_i \in \{\theta_1, ..., \theta_N\}$. It is assumed that productivity is uniformly distributed across firms, which allows for firms to be ranked by their productivity level, such that $\theta_1 < \cdots < \theta_N$. At each productivity level, there are $n(\theta_i) \equiv n_i$ number of homogeneous firms. Thus, the total number of firms in the economy is $\sum_{i=1}^{N} n_i$.

Each period, firms offer jobs that can either be filled by workers or remain vacant. Filled jobs grant firms the flow value of the output produced, less wages paid, while vacant postings provide firms with no value.

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

2.2 Matching

The matching between firms and workers in this economy is characterized by a random search process. Specifically, unemployed and employed workers contact firms with exogenous probabilities λ_0 and λ_1, respectively. All workers sample jobs from an exogenous and discrete job offer or sampling distribution F, with mass f. Thus, the probability of an offer or vacancy arising from any firm with a productivity level θ_i is $\frac{n_i \cdot f(\theta_i)}{\sum_{i=1}^{N} n_i f(\theta_i)}$. This probability represents the product of the number of firms at productivity level θ_i, and the probability of receiving an offer from an individual firm at θ_i, expressed as a share of all offers. I normalize the probability mass function $f(\theta_i)$ to ensure that $\sum_{i=1}^{N} n_i f(\theta_i) = 1$.

On matching, firms and workers produce output that is a function of the firm's productivity, $y(\theta_i)$. Matches are destroyed at an exogenous separation rate δ, in which case the worker flows into unemployment, and the job becomes vacant.

[6] The exposition of the model is related to Jarosch (2023).

2.3 Wage Bargaining

When workers and firms match, they engage in wage negotiations determined by the sequential auction framework by Cahuc, Postel-Vinay & Robin (2006). This framework proposes that if an employed worker contacts an outside firm, competition ensues between the incumbent and the poaching firms for the worker's labor services. While the lower productivity employer offers the maximum pay it can afford by passing on the entire output of the match to the worker, the higher productivity employer can outbid this offer because it produces more. The resulting outcome is that the worker accepts the offer of the firm bidding the higher value. This protocol ensures that the bargained wage implements a split of the match value between the worker and firm, such that the worker receives a share equal to the average of their outside option and the joint match value. In what follows, I describe the wage negotiation protocol by way of an example, first, in the standard infinite firm setting and thereafter, in the finite firm setting.[7]

Consider a worker who is employed at an incumbent firm of productivity $\theta_i \in \{\theta_1, ..., \theta_N\}$, and who previously worked at another firm with productivity $\theta_j \leq \theta_i$. I refer to the value the worker derives from the firm she previously negotiated wages with as her outside option. Wages, denoted by $\omega(\theta_i, \theta_j)$, are negotiated between the incumbent firm-θ_i and the worker based on her outside option at firm-θ_j. Denote the worker's value as $W(\theta_i, \omega(\theta_i, \theta_j)) \equiv W(\theta_i, \theta_j)$, firm's value as $J(\theta_i, \theta_j)$, and the joint value of the match as $V(\theta_i) = W(\theta_i, \theta_j) + J(\theta_i, \theta_j)$.[8] Suppose the worker gets an offer on-the-job from a poaching firm of productivity θ_x. This triggers competition between the incumbent and poaching firms over the worker's labor services. The outcome of the game depends on which firm is more productive and can offer the worker a higher value.

Three cases are possible. First, consider the case when $\theta_x \geq \theta_i$. Then, to retain the worker, the incumbent firm-θ_i revises the worker's wage upwards. The maximum wage firm-θ_i is willing to offer is the entire match output, $y(\theta_i)$. As a result, wages are de-linked from the worker's previous employment at θ_j, and a denoted as $\omega(\theta_i, \theta_i) = y(\theta_i)$. The new

[7]The infinite horizon altering offers game that is the basis of the sequential auctions framework is described in Cahuc et al. (2006). Under the assumptions of costless renegotiation and complete information, the timing of the game is summarized as follows: First, the incumbent and poaching firms make simultaneous wage offers. Second, the employed worker either keeps the offer on hand or chooses the higher wage offer made in the first stage. Third, if the worker chooses the higher wage offer, she makes a counteroffer. In doing so, she uses the chosen offer as a threat point to renegotiate the offer made by the firm with the lower bid. This alternating offers continues between the worker and firms over the infinite horizon. As neither firms bid a wage higher than the output they can produce, the higher productivity firm immediately offers a wage that grants the worker a value that is at least as high as the maximum value that the lower productivity firm can offer.

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

wage grants the worker the entire match value, $W(\theta_i, \theta_i) = V(\theta_i)$, at firm-$\theta_i$. The worker uses this offer of the incumbent firm as her new threat point when bargaining 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, $W(\theta_i, \theta_i)$, and a 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. This share is denoted by $\alpha \in (0, 1)$ and is an exogenous parameter governing the worker's bargaining power in the match:

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

The equation above shows that the value offered to the worker by the poaching firm-θ_x, $W(\theta_x, \theta_i)$, promises at least as much value as the maximum value offered by the incumbent firm-θ_i, $W(\theta_i, \theta_i)$. The worker, therefore, accepts the offer of the poaching firm and makes a job-to-job transition from firm-θ_i to firm-θ_x.

Next, consider the case when $\theta_j < \theta_x < \theta_i$. Now, the poaching firm offers the worker the maximum wage equal to the potential match output $y(\theta_x)$, which comprises the worker's new threat point in place of the one at firm-θ_j. This triggers renegotiation of the current wage between the worker and the incumbent firm. The resulting wage, $\omega(\theta_i, \theta_x)$, offered by the incumbent firm-θ_i re-splits the match value, which leaves the worker with her revised outside option at firm-θ_x, $W(\theta_x, \theta_x)$, 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. Therefore, it is not in the worker's interest to trigger a renegotiation game with the current employer. In this case, the worker stays with the same employer at an unchanged wage.

To summarize, when a worker is employed at some firm-θ_j, and receives an offer from a poaching firm-$\theta_i \geq \theta_j$, the wage negotiated between the worker and firm-θ_i competes with the maximum value that the worker can receive from firm-θ_j. The latter includes the flow value from the match at firm-θ_j, equal to match output, $y(\theta_j)$, and the option value of on-the-job search from firm-θ_j. In an infinite firm setting, on-the-job search from firm-θ_j includes the possibility of receiving offers from firm-θ_i *and* firm-θ_j. In other words, when the worker is bargaining with poaching firm-θ_i using an offer from firm-θ_j as her outside option, the worker's set of potential offers on-the-job at firm-θ_j contain, with non-zero probability, two unlikely matches: First, the possibility of a next-period match with the incumbent firm-θ_j. This means the worker can receive an offer from their firm while employed at that firm. Second, the possibility of a next-period match with the poaching firm-θ_i. In other words, while the worker negotiates wages with the poaching firm-θ_i using the offer from firm-θ_j as their threat point, firm-θ_i competes with the possibility of the worker sampling its offer again in the future which lies in the worker's outside option.

In a finite firm framework where each firm has a non-zero share in the offer distribution, I make two assumptions that remove the aforementioned offers. First, I assume a worker cannot receive an offer on-the-job from their own firm. Thus, the worker employed at a firm at productivity-θ_i can get a poaching-firm offer from any firm outside of that productivity, θ_{-i}, as well as any of the remaining $n_i - 1$ 'peer' firms, defined as firms at the same productivity level as the incumbent firm-θ_i. If the worker receives an offer from one of the peer firms at θ_i, the incumbent and poaching firms compete and offer the same value to the worker, thereby making the worker indifferent between the two offers. In such an instance, I assume the worker faces an exogenous probability ν of making a job-to-job transition from the incumbent to the poaching firm.[9]

Second, I assume that while bargaining with the worker, the poaching firm-θ_i is allowed to retaliate against the worker by removing its future offer from the worker's outside option at firm-θ_j. In other words, should the wage negotiation between the worker and firm-θ_i break down, leading the worker to avail her outside option at firm-θ_j, then she does not receive the option value of matching with firm-θ_i again through on-the-job search at firm-θ_j. This has the effect of discounting the worker's outside option and the resulting wage negotiated between retaliating firm-θ_i and the worker. Thus, in the spirit of Jarosch, Nimczik & Sorkin (2023), I assume that firms do not allow their matched applicants to reapply to them again from their outside option.

In the context of retaliation, a few points are noteworthy. First, the penalty imposed on the worker does not occur in equilibrium, as the negotiation between the worker and the retaliating firm-θ_i never breaks down. Despite that, this mechanism affects the equilibrium wage outcomes of the model. Second, I assume that the penalty imposed on the worker only lasts for one employment spell, i.e., the worker is penalized from getting an offer from firm-θ_i only as long as she is employed at firm-θ_j. However, once her employment spell

[9]To the extent that job-to-job mobility is costly, yet a substantial fraction of job switches tend to occur without wage increases, the probability of switching to a peer firm despite the same wage offer can be micro-founded by introducing non-wage amenities in the model as in Sorkin (2018), Hall & Mueller (2018), Mercan & Schoefer (2020).

at firm-θ_j ends, firm-θ_i forgets about the retaliation. This limited memory assumption of firms is made to ensure the model remains tractable. Finally, it is also worth highlighting that during wage negotiations between the incumbent and poaching firms, only the higher productivity firm-θ_i has the incentive to retaliate against the worker. This is because the lower productivity firm-θ_j will choose to make its best offer as attractive as possible to make the winning bid and secure the worker's acceptance. Consequently, it is sub-optimal for firm-θ_j to offer a lower wage that involves retaliation.[10] It, however, is optimal for the higher-productivity firm-θ_i to retaliate against the worker as it offers a value that is higher than the best offer of the losing firm.[11]

To account for retaliation, when negotiating wages with firm-θ_i, the worker's outside option is now represented as $\widetilde{W}(\theta_j, \theta_j, \theta_i)$. The latter is the match value offered by firm-θ_j that no longer includes the option value of matching with firm-θ_i through on-the-job search at firm-θ_j. In light of this, I re-specify the wage setting equations (1) and (2) as follows:

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

Equation 3 shows that the value offered by firm-θ_i to a worker with an outside option at firm-$\theta_j \leq \theta_i$ contains two terms. The first is the joint value offered by firm-θ_j, keeping track of the retaliation the worker will face by firm-θ_i should she accept firm-θ_j's offer. The second term is the increment in joint value due to the worker switching from firm-θ_j to firm-θ_i, weighted by the worker's bargaining power parameter. This expression is an outcome of Nash bargaining between the worker and the poaching firm and is formally derived in the Appendix A.1.

Finally, the discussion above can be generalized to unemployed workers. The

[10] To illustrate this point, the sequential auctions follow similarly as the case with infinite firms. Initially, both firms simultaneously make offers to the worker. The worker can then either keep the offer at hand or choose the higher of the two offers. If the worker chooses the latter, she makes a counteroffer to the lower-value bid of the losing firm, using the higher-value bid of the winning firm as a threat point. If the losing firm retaliates against the worker, then the threat point includes a continuation value from the winning firm that precludes an on-the-job offer from the losing firm.

Just like the infinite firm setting, the outcome of the game is that the higher productivity firm outbids the lower productivity firm's offer. As such, retaliation by the lower productivity firm is not credible, and it is optimal to abstain from retaliating to increase its offer's attractiveness. Consequently, the losing firm does not retaliate and instead offers the worker the entire match value. On the other hand, the higher productivity firm opts to retaliate. It immediately provides the worker with a value that is at least as high as the maximum value afforded by the losing firm.

[11] Note that in the context of homogeneous workers, it is optimal for the higher-productivity firm to retaliate against an applicant by not making a future offer if the retaliated applicant is not the only applicant who matches with the firm. I assume that the probability of the firm matching with a solo applicant and the latter being the retaliated applicant is zero. Jarosch et al. (2023) compute this probability using data from Austria and find the likelihood of a worker being the only applicant for a job to be approximately zero.

model allows firms to retaliate against workers who negotiate wages from the state of unemployment. The unemployed worker receives a flow value from leisure and the option value of searching from unemployment. I assume that the retaliating firm removes its future offer from the unemployed worker's continuation value, thereby reducing the option value of job search from the state of unemployment. As in the case of the employed worker counterpart, I assume that the retaliation only lasts for one spell of unemployment.

To see this, suppose an unemployed worker matches with firm-θ_i. Denote the outside option of such a retaliated unemployed worker who does not receive the option value from matching again with firm-θ_i as $\widetilde{U}(\theta_i)$. Then the reservation wage negotiated by the unemployed worker and firm-θ_i solves:

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

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

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

2.4 Value Functions

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

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

The employed worker receives a flow payoff equal to the current wage, $\omega(\theta_i, \theta_j)$. In the next period, the worker may exogenously separate from the firm with probability δ and flow into unemployment, receiving a value U. If she stays employed, she may contact and sample an offer from a firm with productivity θ_x, with probability $\lambda_1 n_x f(\theta_x)$. If the productivity of the new firm-$\theta_x > \theta_i$, then the worker makes a job-to-job transition to firm-θ_x. This results in a value, $W(\theta_x, \theta_i)$, reflecting that the worker is employed at firm-θ_x and her wage is benchmarked against her prior employer-θ_i. If $\theta_i > \theta_x > \theta_j$, the worker gets a within-job wage revision, and now her value, $W(\theta_i, \theta_x)$, reflects her new outside option, θ_x, whereas the current employer remains the same. 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. Her value function is not affected by whether she remains at the same job or switches jobs because she realizes the maximum value from the match, $W(\theta_i, \theta_i)$, in both cases. Finally, with the remaining probability, she does not match with any firm or matches with a firm that is less productive than θ_j or matches with her own employer again – in all such cases, her value remains unchanged.

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

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

To retain the worker, firm-θ_i bids up the wage to its maximum level, such that the worker gets the entire match output, $y(\theta_i)$. The option value of search excludes the possibility of sampling a job from a firm with productivity θ_h. This is shown in the third line where the worker's value from a firm at θ_h is removed from the potential offers that she can receive on the job. Note that the preclusion of firm-θ_h's offer only lasts through the worker's employment spell at firm-θ_i. If the worker joins any other firm or gets matched with a firm at the same productivity, her value function is no longer $\widetilde{W}$ but W and does not keep track of firm-θ_h. This is due to the limited memory assumption of the firm described in the last section. This simplifying assumption reduces the dimensionality of the value function by preventing the need to keep track of the full history of precluded firms from the worker's offer distribution. Finally, if the worker gets an offer from any of the remaining firms at θ_i, she is released from the retaliation of firm-θ_h and receives a value of $W(\theta_i, \theta_i)$, irrespective of whether she chooses to stay at the incumbent firm or moves to the poaching firm.

The value function of an unemployed worker satisfies:

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

The unemployed worker receives a flow payoff from leisure, z, and with probability λ_0, contacts a firm. If that firm is more productive than an unknown threshold productivity level, θ_u, the worker accepts the job and flows into employment.[12] With the remaining probability, including not receiving a job offer or receiving one from a firm at or below θ_u, the worker remains in the state of unemployment.

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

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

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.[13]

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

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

The flow payoff to the firm from a match is equal to the output, $y(\theta_i)$, less the wages 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 from the job is zero. If the firm and worker do not separate, and the worker samples an offer from a firm that is less productive than θ_i, but more productive than θ_j, then the match value is

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

[13] An 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.

re-split, and the firm receives a revised share, $J(\theta_i, \theta_x)$, reflecting the new outside option of the worker. 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 value. 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.[14]

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 can be solved combining equations (3)-(9). The model solution is described in the next section.

2.5 Solving the Model

The value functions in equations (5)-(9), along with solutions to Nash bargaining in (3) and (4) can be expressed in terms of a functional equation − the joint value function − defined as the total match value between a worker and firm, $\widetilde{V}(\theta_i, \theta_h), \forall h \geq i$. When $h = i$, the joint value takes the form, $\widetilde{V}(\theta_i, \theta_i) = V(\theta_i)$. The value from unemployment can also be expressed in terms of joint value at firm-θ_u, $U = V(\theta_u)$. Thus, the model can be expressed in terms of the following two equations:

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

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

The left-hand side of the equation 10 is the present discounted joint value of a match

[14] Throughout the model, the value to the firm of keeping a job opening vacant is assumed to be zero. This is akin to a free-entry condition. With this assumption, the entire model can be solved without specifying the firm's value from keeping a job-opening vacant. In a version of this model with an endogenous vacancy creation decision, this condition can be achieved by assuming that the cost of posting a vacancy to a firm is firm productivity-specific as in Jarosch et al. (2023). See Berger et al. (2023) and Gouin-Bonenfant (2022) for the effect of firm competition on vacancy posting. See Lise & Robin (2017) and Bagger & Lentz (2019) for vacancy creation in the Postel-Vinay & Robin (2002) setup.

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

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

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

2.6 Labor Market Flows

The model is solved in steady state such that inflows from employment and unemployment balance. The laws of motion of employment and unemployment are derived in Appendix A.4. Denoting the total stock of unemployed workers as u, the law of motion of unemployment is:

$$\delta(1-u) = u\lambda_0 \sum_{x=u+1}^{N} n_x f(\theta_x) \tag{12}$$

Inflows to unemployment comprise separations of employed workers, $1-u$. Workers transition out of unemployment when they receive an offer from any firm with productivity above their reservation productivity level.

Denoting the total number of workers at a firm with productivity-θ_i as $E(\theta_i)$, the law of motion of employment at such a firm-θ_i is given by:

$$u\lambda_0 f(\theta_i) + \lambda_1(1-\delta)\Bigg(f(\theta_i)\sum_{j=u+1}^{i-1} n_j E(\theta_j) + f(\theta_i)\cdot\nu\cdot(n_i-1)E(\theta_i)\Bigg)$$
$$= E(\theta_i)\Bigg(\delta + (1-\delta)\lambda_1\Bigg(\sum_{x=i+1}^{N} n_x f(\theta_x) + \nu(n_i-1)f(\theta_i)\Bigg)\Bigg) \tag{13}$$

The inflows to firm-θ_i are shown on the left-hand side of equation 13. The first term represents inflows from unemployment to firm-θ_i. The second and third terms represent inflows from employed workers who are not separated and match with firm-θ_i. Specifically, the second term represents inflows from firms with productivity less than θ_i. In contrast, the third term represents inflows from the remaining peer firms at θ_i who make a job-to-job switch with probability ν.

The right-hand side shows the outflow of workers from firm-θ_i. The first term represents all the workers who flow out to unemployment due to the match breaking up. The remaining terms capture job-to-job flows out of firm-θ_i, either to a more productive firm or to the remaining peer firms at θ_i.

2.7 Understanding the Model Mechanisms

By expressing the law of motion of employment, we can define the Employer-to-Employer separations for firm-θ_i, denoted as $EE^-(\theta_i)$, as:

$$EE^-(\theta_i) = E(\theta_i)\lambda_1(1-\delta)\Bigg(\underbrace{\sum_{x=i+1}^{N} n_x f(\theta_x)}_{\text{vertical EE}} + \underbrace{(n_i-1)f(\theta_i)\nu}_{\text{horizontal EE}}\Bigg) \tag{14}$$

The expression provides several insights into the model's mechanisms pertaining to the effect of firm competition on EE transitions. First, unlike the standard infinite firm setting, a model with finite firms distinguishes between vertical and horizontal EE transitions. Vertical transitions represent upward movement on the job ladder, while horizontal ones refer to moves to peer firms at the same productivity level.

Second, a reduction in the number of firms decreases EE transitions. In the extreme case of a single firm in the labor market (i.e., the incumbent firm, $n_i = 1$ and $n_{-i} = 0$), the worker cannot make either vertical or horizontal transitions as all vacancies arise from the incumbent firm, and workers cannot receive an offer from their own firm by assumption.

Third, changes in the number of firms affect horizontal EE transitions. This happens because as the number of firms, n, at any productivity level changes, the vacancy share of each firm, $f(\theta)$, adjusts to hold $n \cdot f(\theta)$ fixed. In particular, a decrease in the number of firms, n_i, increases $f(\theta_i)$, causing $EE^-(\theta_i)$ to decrease. This implies that workers employed at larger firms face a lower probability of making EE transitions as a larger share of job offers lie within the worker's own firms, resulting in a smaller share of offers outside their firm. In Section 3.2.1, I discuss this channel of the model further and term it the 'mega-firm' channel – as the number of firms in the labor market decreases, each firm becomes larger, and workers face a lower probability of transitioning out of their own firms.[15]

Finally, the assumption of retaliation has no impact on EE transitions in the model. This happens because retaliation occurs in the off-equilibrium and does not affect realized transitions in the model. Recall that if a worker chooses the less productive firm's offer over the more productive firm's offer, the latter retaliates by not allowing the worker to apply for their vacancy in the next period. However, in equilibrium, the worker always chooses the more productive firm's offer, which means they are never barred from making EE transitions due to retaliation. Section 3.2.1 demonstrates the null effect of retaliation on EE transitions.

Even though firm size and retaliation have distinct implications on EE transitions, they work together to reinforce their effect on wages. This interaction leads to an amplified wage response in the model. Equation A.3 expresses wages as a function of the equilibrium joint value functions of the model. The equation shows that the equilibrium wage to a worker employed at a firm-θ_i, and having an outside option at a firm-$\theta_j \leq \theta_i$, reflects a flow and a continuation value. The flow value equals the weighted average of the match output produced by the worker and firms-θ_j and θ_i. The continuation value reflects the weighted average of the joint option value to the worker and firm when the worker searches on-the-job from firms-θ_j and θ_i. The continuation value deducts the value the worker receives from searching on-the-job from their current employer. This is the compensating differential that the worker pays their employer for being able to search on the job from firm-θ_i and realizing a wage increase in the future.

The expression in equation A.3 also sheds light on the model mechanisms of retaliation and firm size pertaining to wages. A worker getting retaliated by firm-θ_i does not derive the option value of matching with firm-θ_i while searching on-the-job from firm-θ_j. This is shown in the second line of equation A.3, which deducts the joint value of matching with

[15]In other words, in the model, changes in EE transitions emanating from varying the number of firms are not productivity-enhancing moves up the job ladder but rather turnover across peer firms. To make vertical moves responsive to changes in the number of firms would involve introducing other dimensions to the job ladder, such as stochastic match-specific productivity that evolves during the match or job-specific amenities.

firm-θ_i from the set of outside offers the worker could receive at firm-θ_j. Further, the effect of retaliation is amplified by firm size. The larger the size of the retaliating firm due to a larger share of offers, $f(\theta_i)$, the higher the loss in wages due to retaliation. Section 3.2.1 examines the implications of firm size and retaliation on average wage levels and wage growth of job stayers and switchers.

3 Quantitative Analysis

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

3.1 Calibration

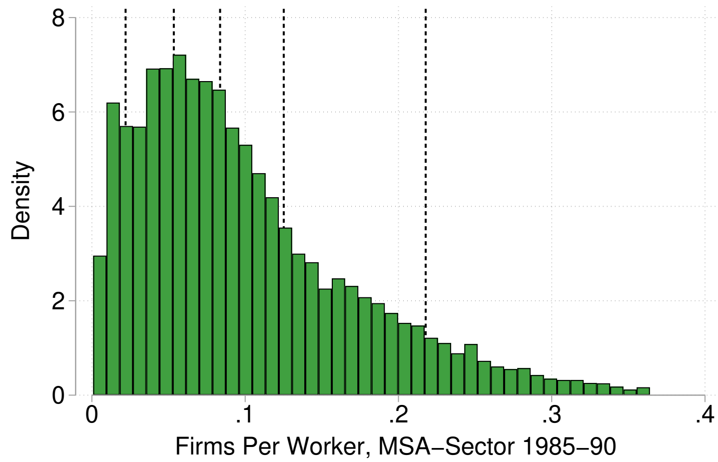
The model is calibrated at a monthly frequency, with the economy assumed to be in a steady state. The model's moments are targeted to match the long-run averages of empirical moments for the US economy. Specifically, the model is calibrated to reflect the economy from 1985 to 1990 and then evaluated against the economy from 2012 to 2017.[16] In what follows, I describe the empirical moments targeted in the calibration exercise and explain how they are informative about the model's parameters.

Contact rates of employed, unemployed and separation rate: The monthly transition probability from employment-to-employment (EE), and unemployment-to-employment (UE) are informative about the contact rates of the employed (λ_1) and unemployed (λ_0), respectively. The employment-to-unemployment (EU) flow probability is tightly linked to the exogenous separation rate, δ.

To calculate the long-term averages of the UE and EU transition probabilities, I follow the methodology of Shimer (2012) and use stocks of unemployment duration from the monthly Current Population Survey (CPS) from 1985m3-1990m3. The monthly UE hires probability is computed by subtracting from the number of unemployed individuals in the previous month the number of workers who have been unemployed for more than a

[16] The chosen periods have similar unemployment rates (around 6.2 percent) but considerably different levels of employer competition (discussed in the next section). It is worth noting that the results of the calibration exercise remain qualitatively similar even when the model is calibrated to target long-term averages of the 2012-17 economy and evaluated against the 1985-90 economy.

Figure 2: Distribution of Firms Per Worker across MSA-sectors of the US, 1985-90



Notes: Business Dynamics Statistics. This figure displays the distribution of the long run average of firms per worker across MSAs and 2-digit NAICS sectors of the US between 1985-90. The black dotted lines plots quintiles of the distribution.

month to arrive at the number of workers who exited unemployment from the last month to the current month. This value is expressed as a fraction of the number of unemployed workers in the previous month. The EU separations probability is calculated by plugging the UE hires probability into the steady-state unemployment rate. I arrive at monthly UE and EU transition probabilities averaging 44.9 percent and 3.78 percent, respectively.

To compute the monthly EE transition probability, I follow the approach of Diamond & Şahin (2016), which builds on the methodology developed in Blanchard, Diamond, Hall & Murphy (1990) that uses EE transition measures of the Annual Social and Economic (ASEC) Supplement of the CPS. The annual estimates are linearly interpolated to arrive at quarterly measures of EE transitions, which are then expressed as a monthly probability. I take the long-run quarterly averages of the monthly EE transition probability over the period 1985q1-1990q1. The EE transition probability over this period averages 2.83 percent.

Total number of firms: The total number of firms in the model is the sum of firms over the productivity distribution, expressed as $\sum_{i=1}^{N} n_i$. The value of N, representing the number of productivity levels, is determined based on the average number of levels in a worker's lifetime job ladder, which is assumed to be five. This value falls within the range reported in the literature on internal career ladders, with studies by Forret & Dougherty (2004) and Caliendo, Monte & Rossi-Hansberg (2015) suggesting four levels, while Bayer & Kuhn (2018) find five levels. It should be noted that this value does not include θ_u, which is considered a non-employer productivity level.

In order to estimate the total number of firms across the N productivity levels, I utilize the firms per worker across metropolitan area-sector pairs in the years 1985-90, as shown in Figure 2. I use this distribution to define a labor market as a Metropolitan Statistical Area (MSA)-sector in the model. This is the most granular publicly available data on firms per worker and some model outcomes dating back to 1985. To determine the number of firms in the model from the distribution of firms per worker, I first approximate the firms per worker distribution by its quintiles (shown by the dashed lines in Figure 2). I assume that each quintile represents an individual and isolated market in the model that differs from one other only in terms of the number of firms. Second, I arrive at the number of firms in each market by assuming that each market faces approximately 5000 workers. This was the average employment in an MSA-sector cell in 1985-90. I arrive at the number of firms in each market to be $\{109.8, 267.2, 418.1, 625.8, \text{and } 1151.3\}$.[17] This method of determining the number of firms enables the model to capture the dispersion in the distribution of firms per worker rather than focusing only on its mean or median. Moreover, this approach allows the model to account for the non-linear response of its outcomes to changing firms per worker prevalent in markets with smaller firms. Focusing on the distribution of firms per worker also allows the model to get as close as possible to the notion of the number of firms in local labor markets.

Once the number of firms in each market is determined, the model is solved and simulated individually for each market. Finally, the aggregate moments in the model are computed by taking a weighted average of market-level moments. The weights correspond to the employment share in 1985-90 of each quintile of the empirical firms per worker distribution shown in Figure 2.

To allow the market-specific number of firms to take on decimal values, I express each market as a combination of several markets with an integer-valued number of firms. For instance, if the total number of firms in a market is distributed over a two-dimensional productivity grid ($N = 2$), I use a weighted average of four markets with an integer-valued number of firms to express that market's firms in decimal value. The weights are uniquely determined by the difference between the decimal value and the largest or smallest integer value.[18]

Distribution of firms over the job ladder: After establishing the number of firms in

[17]Even though the number of firms determined might appear large for the model to start behaving as if it is in an infinite-firm setting, these firms are distributed over the job ladder in a way that the number of firms at the top that have the most bite in terms of the response of outcomes, is very small. As a result, the model's outcomes respond to the changing number of firms despite the large total number of firms. I discuss distribution of firms over the job ladder below.

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

each market, the subsequent step is determining their distribution across the job ladder. I set the five-dimensional vector $\{n_i/\sum_{i=1}^{N} n_i\}_i$ to match the distribution of firms over the job ladder. I approximate the job ladder by the firm size distribution, conditional on firm age and sector. The firm size is measured by the size of the workforce. Even though most search models featuring a job ladder postulate a positive relationship between firm size and productivity, Haltiwanger et al. (2018) observe evidence of a firm size ladder only after controlling for firm age. I, therefore, compute the firm size distribution averaging over firm age groups and sectors. I use firm and employment counts in firm size, age, and sector cells from the BDS to estimate the number of firms per worker over the firm size ladder. The data on firm age are prone to being left-censored, and many of the firm age $\times$ size cells have missing values due to Census disclosure norms. To avoid the problem of left-censoring, I exclude all firm age data prior to 1988. To tackle the problem of missing observations, I aggregate the data into five firm size bins: 1-9, 10-19, 20-99, 100-499, and 500+ employees and three firm age bins: 1-5, 6-10, and 11+ years.[19] I fill in the missing firm age $\times$ firm size $\times$ sector cells by imputing their differences from the recently available data on coarse firm age and firm size bins provided by the BDS. Finally, I take employment-weighted averages of the firm size classes over all the firm age-sector cells to arrive at the firm size ladder for 1987-89. The main advantage of using a firm-size ladder to proxy for the job ladder is the availability of data dating back to the 1980s. I arrive at the following distribution of the share of firms over the firm size bins: {0.612, 0.143, 0.166, 0.049, 0.027}, also shown by the blue bars in Figure 4a. This distribution governs the firm share over the five-tier job ladder in each of the markets.[20] It distribution indicates that most employers in the sample belong to the least productive tier of the job ladder, while only a small proportion (3 percent) are situated at the top of the job ladder.

Job offer distribution: Next, I set the job offer distribution to be beta with shape

the market as a weighted average of four markets with integer-valued number of firms:

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

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

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

[20] In particular, it leads to the following division of firms over the job ladder. In Market 1: {67.3, 16.1, 18.2, 5.4, 2.9}. Market 2: {163.6, 39.1, 44.2, 13.2, 7.1}. Market 3: {256.0, 61.1, 69.2, 20.6, 11.1}. Market 4: {383.2, 91.5, 103.6, 30.9, 16.6}. Market 5: {704.9, 168.3, 190.6, 56.8, 30.6}.

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

Finally, the discount rate, γ, is set to match an annual interest rate of four percent. I set ν, the probability of workers switching to a peer firm, to 0.5. In other words, workers are equally likely to stay in their firm or switch firms upon encountering an offer on-the-job from a firm of the same productivity as their incumbent firm. Output across all matches, $y(\theta_i)$, is expressed as θ_i additively scaled up by a constant output shifter, ζ_i. This is done so that the least productive firm produces non-zero output. I set the output shifter to 1. In the calibrated model, this implies the ratio of the flow value from leisure, net of the output shifter and as a fraction of the Average Labor Productivity (ALP) is in line with the target range set in the literature (Shimer (2005), 0.4; Mas & Pallais (2019), 0.6; Hall & Milgrom (2008), 0.71 and Hagedorn & Manovskii (2008), 0.995).

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

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

Table 1: Parameter Values

	Parameter	Value	Target/Source
		Externally Calibrated	
N	Productivity Levels	5	Bayer & Kuhn (2018)
$\sum_{i=1}^{N} n_i$	Mean Firms Across Markets	266	Emp-weighted FPW dist., MSA×Sector (BDS)
$\{n_i / \sum_{i=1}^{N} n_i\}_i$	Firm share|Job ladder	{0.61, 0.15, 0.17, 0.05, 0.03}	Firm share|Firm Size dist. (BDS, 1987-89)
γ	Discount Rate	0.004	4% annual interest rate
		Internally Calibrated	
λ_0	Contact Rate of Unemp	0.40	E [UE]
λ_1	Contact Rate of Emp	0.09	E [EE]
δ	Separations Rate	0.04	E [EU]
η, μ	Job Offer Distn $\sim$ Beta	1.03, 0.74	SD (Log Wage Offers); wΔ|Job Spell
α	Worker's Bargaining Share	0.45	Mean-min Ratio
z	Flow value of leisure	0.75	z/Average Labor Productivity

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

Table 2: Model-generated Moments and their Targeted Values

Moment	Model	Data	Data Source
E [UE], %	40.4	44.9	CPS, 1985-90
E [EE], %	2.88	2.83	CPS, 1985-90
E [EU], %	3.99	3.79	CPS, 1985-90
SD (Log Wage Offers)	0.23	0.24	Hall & Mueller (2018)
E [Wage Growth, 12m Job Spell], %	0.57	0.90	SIPP, 1996-00
Mm Ratio	1.49	1.5-2	Hornstein, Krusell & Violante (2011)
z/ALP	0.39	0.40	Shimer (2005)

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

the targeted and model-generated moments as well as its fixed parameters. Table 2 reports the simulated moments of the model at the calibrated parameters and their targeted counterparts. The model moments come close to delivering their targeted values.

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

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

3.2 Equilibrium Effects of Declining Number of Firms

This section analyzes the model's implications when the number of firms varies from its baseline level. In particular, holding productivity of each firm constant and all parameters at their calibrated values, I understand the effect of changing number of firms on the equilibrium outcomes of the model. I first explain the qualitative implication of the model and evaluate the model's main mechanism. I then show the quantitative predictions of the model to different experiments involving changing the number of firms.

3.2.1 Qualitative Implications of the Model

Figure 3 plots labor flow and wage moments generated by the model when the number of firms, n_i, at each productivity level is varied by the same proportion. Specifically, the number of firms across different productivity levels and markets is scaled proportionally by the following factors: 0.4, 0.5, 0.75, 1.25, 1.5, 1.75, 2, 2.25, and 2.5. All other parameters of the model are held fixed to their values shown in Table 1. The vertical line represents the calibrated model where the employment-weighted average number of firms across all model markets is set to 266. The benchmark model, described in Section 2, is shown by the solid red line. Each of the subsequent lines plots various versions of the model, shutting off the effect of its different channels. In what follows, I first discuss the comparative statics of changing the number of firms in the benchmark model and then examine model mechanisms.

3.2.1.1 Benchmark Model

The solid red line in Figure 3a shows that the average EE transitions rate increases in the number of firms. As the number of firms on the job ladder uniformly declines, employees of these firms face a lower probability of receiving offers from poaching firms at the same productivity level. This reduces worker propensity to quit and make EE transitions. In the extreme case, suppose the most productive tier of the job ladder comprises only one firm; then, all employees of that firm lose the option of making a job switch. As the most productive firms are also the largest in the model, a higher share of employees is prevented from making EE transitions if the incumbent firm faces no competition. On the other hand, as the competition intensifies, the probability of receiving an offer from a firm at the same productivity level increases resulting in a higher number of quits.

The solid red line in Figure 3b shows the average level of wages, relative to productivity, is also increasing in the number of firms. This happens for two reasons: First, average real wages are a function of the joint match value between the worker and the incumbent firm. As the number of firms in the labor market decreases, so does the option value of on-the-job search from the incumbent firm. This reduces the joint value of the match and, therefore, decreases the average wages relative to productivity. Second, the strong non-linearity in the plot is due to firms imposing a penalty on re-applicants. In an environment with many firms in the market, each firm has a lower share in the offer distribution, and the market converges towards one with atomistic firms. This diminishes firms' ability to penalize workers by removing their offers from workers' outside options. Thus, competition intensifies with an increasing number of firms trying to poach and retain workers, increasing workers' value and bidding up wages. However, the opposite is true as competition dampens. Suppose there is a single firm at a given productivity level, and that firm's vacancy is precluded from the worker's job search. In that case, the worker faces a reduction in their job-finding probability that is tantamount to losing a tier of the job ladder. This leads to a considerable decrease in wages.

The growth rates of wages associated with job stayers and switchers are shown in figures 3c and 3d, respectively. As competition in the economy increases, workers are more likely to get higher wage offers from poaching firms. In trying to match such offers, incumbent firms offer the maximum wage they can afford to retain the workers, leading to a higher average wage level for stayers. As a result, workers increasingly receive a within-job wage increase as employer competition increases, resulting in the rising wage growth of job stayers. At the same time, workers face a higher likelihood of maxing out on their wages as job stayers, which means wage growth associated with job switches is lower if the number of firms is high. At the other end of the spectrum, when workers face fewer firms, they are much more likely to stay longer on the same job and at a suppressed wage, such that there is more room for wages to increase when workers switch jobs. In Section 4.2.3, I show descriptive evidence of the distinct response of the wage growth of job stayers and switchers, both in magnitudes and signs, to varying firms per worker.

3.2.1.2 Main Mechanisms of the Model

The main channels through which the changing number of firms drives the model outcomes can be summarized as the following: (1) *Mega Firm Channel*: For a given distribution of firms and offers over the job ladder, a decrease in the number of firms makes every firm larger. As employment and offers become concentrated in large firms, workers in these firms face a reduced probability of finding a job outside their firm. This reduces the worker's value from searching on-the-job from the incumbent firm. (2) *Retaliation Channel*: Workers can no longer match with the incumbent firm from their outside option, thereby reducing the option value of on-the-job search from the worker's outside option. When negotiating wages with the incumbent firm, the worker has a lower threat point, which reduces the worker's share of the joint value. Note that both model mechanisms are enabled through the worker searching on the job, either from the incumbent firm or their outside option:

The benchmark version of the model described in Section 2 allows for the Mega Firm and Retaliation Channels. In this model, the distribution of firms over the job ladder, $\{n_i / \sum_{i=1}^{N} n_i\}_i$, is skewed to the right leading to the very large and productive firms at the top of the ladder. Workers cannot re-apply to firms they have turned down, leading to retaliation. It is useful to consider how the model behaves in the absence of these channels to understand how each channel and its interactions affect model outcomes. This involves constructing three different economies that are distinct from the benchmark model. In each of these economies described below, all other parameters are held fixed to their values given in Table 1.

Allowing Mega Firms Channel Only: This version of the model no longer allows firms to retaliate in the benchmark model. In other words, firms no longer penalize workers for turning their offers down. Both unemployed and employed workers can re-apply to the vacancy of the firms they are bargaining with, from their outside options. This model allows wages to be set as in equation 2 instead of 3, i.e., the worker's outside option contains the option value of matching with the incumbent firm again. I describe the model's value functions in Appendix A.5.

Allowing Retaliation Channel Only: This model version allows firms to retaliate, but it shuts the mega-firm channel that is enabled through the skewed distribution of firms over the job ladder. In other words, this model version is the same as the benchmark model in section 2, with one exception. Instead of assuming the firm distribution over the job ladder, $\{n_i / \sum_{i=1}^{N} n_i\}_i$ is {0.61, 0.15, 0.17, 0.05, 0.03} as shown in Table 1, the model assumes all firms are distributed uniformly over the job ladder, i.e., $\{n_i / \sum_{i=1}^{N} n_i\}_i$ is {0.2, 0.2, 0.2, 0.2, 0.2}. Thus, relative to the benchmark model that uses the right-skewed distribution of firms, this model version allows the share of firms to be equalized across all productivity levels.

Switching off Mega Firm and Retaliation Channels: This model version switches off retaliation and mega-firms by using the version of the model detailed in Appendix A.5. In that model version, it assumes that firms are uniformly distributed over the productivity grid, i.e., $\{n_i / \sum_{i=1}^{N} n_i\}_i = \{0.2, 0.2, 0.2, 0.2, 0.2\}$.

Figure 3 plots the three distinct versions of the model: (1) Model with mega firms only that shuts down the retaliation channel (blue dashed line), (2) Model with retaliation only that shuts down the mega-firm channel (green dash-dotted line), and (3) Model that shuts down mega firms and retaliation (black dotted line). Across each model variant, I hold all the other parameters of the model constant to their values in Table 1 and allow the outcomes to only vary with the number of firms.[21]

Figure 3a shows that the EE transitions rate is increasing in the number of firms across the two versions of the model, with and without mega-firms. Compared to a model with

[21] Just as in the previous section, the number of firms across all productivity levels and markets is adjusted proportionately based on the following factors: 0.4, 0.5, 0.75, 1.25, 1.5, 1.75, 2, 2.25, and 2.5.

uniformly distributed firms (black dotted line), in a model with mega-firms (red solid line), firms at the top of the job ladder are fewer and larger. Thus, for a given number of firms, the level of EE transitions is lower in a model with mega-firms. As the number of firms further decreases along the x-axis, the model with mega-firms gravitates towards one with a single firm at the highest tier of the job ladder, thereby amplifying the decline in EE transitions. This effect is attenuated in a model without mega firms. Note that the retaliation channel does not affect any realized worker transition; therefore, the EE transitions rate in models with and without retaliation coincide.

Figure 3b shows that across all versions of the model, wages/productivity are non-decreasing in the number of firms. The retaliation and mega-firm channels independently are less important in generating a wage response to a changing number of firms. Their interaction amplifies the wage response relative to a model without these channels. This means that for an individual worker, the wage penalty of retaliation is considerably worse in an economy with fewer firms, in which the firm imposing the penalty is large. Retaliation is less crucial in a model where firm competition is high, either due to a higher number of firms or through the absence of mega firms.

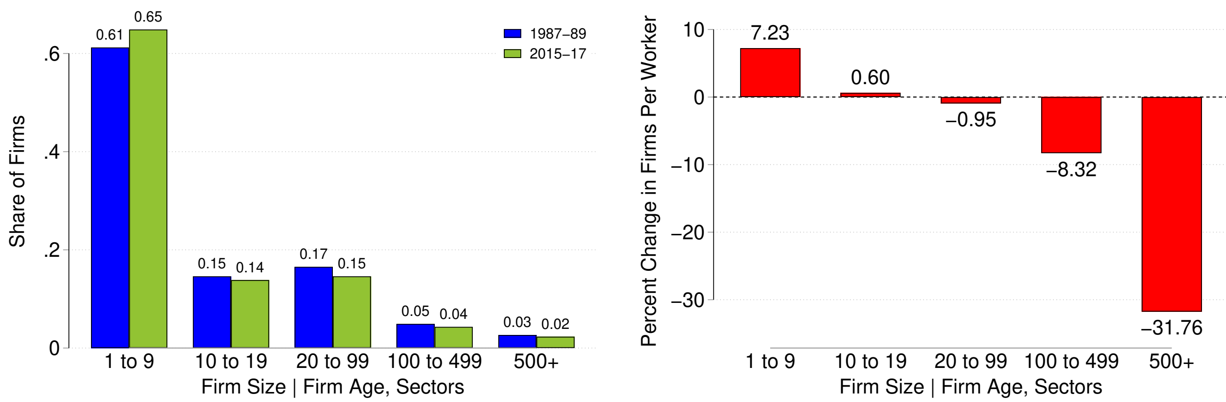
Figures 3c and 3d show that, for all versions of the model, the wage growth associated with continuous job spells is small and positively related to the number of firms. In contrast, that associated with EE transitions is large negatively related to the number of firms. To understand the model behavior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

Next, hold the retaliation channel constant and compare the models with mega firms (solid red line) and without mega firms (dashed-dotted green line). For a given number of firms, the model with mega-firms has less competition among firms. Thus, in a model with mega-firms, relative to one without, we see higher wage growth of job switchers and lower wage growth of job stayers. Notice that this follows intuitively from Figure 1c, where in an environment of low competition due to fewer firms, the wage growth of job switchers is high. This explains why for the job switchers, the solid red line (with mega-

Figure 4: Firm Share and Changes in Firms Per Worker over the Firm Size Ladder

(a) Firm Share over Firm Size Bins, 2015-17 and 1987-89

(b) Firms per Worker over Firm Size Bins, Changes in 2015-17 relative to 1987-89



Notes: The left figure shows the firm share over the firm-size ladder in 1987-89 and 2015-17. The right figure shows the changes from 2015-17 to 1987-89 in the long-run average of the ratio of the number of firms to workers over firm size classes. Source: Business Dynamics Statistics.

firms) is above the dashed-dotted green line (without mega-firms), and the dashed blue line (with mega-firms) is above the dotted black line (without mega-firms). This also explains why for the job stayers, the opposite holds: the solid red line (with mega-firms) is below the dashed-dotted green line (without mega-firms), and the dashed blue line (with mega-firms) is below the dotted black line (without mega-firms).

3.2.2 Quantitative Implications of the Model

In this section, I quantify the model's implications on wages, and EE transitions when the number and distribution of firms is varied by the extent to which it changed in the US economy between 1985-2017. Specifically, I undertake the following experiments: (1) Simulate the same change in the firm share over the job ladder in the model observed in the data between 1987-2017. (2) Simulate a 13.1% decrease in the number of firms at each productivity level observed in the aggregate US economy from 1985. (3) Simulate an asymmetric change in the number of firms over the productivity distribution. Across all experiments, I hold all other parameters of the model constant to their values given in Table 1. In what follows, I first describe each of the three experiments and their combinations, then discuss the results.

I. Changing the distribution of firms over the job ladder: A key ingredient of the model is the right-skewed distribution of firms over the job ladder, which leads to a small number of large and highly productive firms. Few large firms at the top of the job ladder amplify the mega-firm and retaliation channels. The baseline calibration of the model approximated the firm distribution over productivity levels by the share of firms over firm size classes, conditioning on firm age and sector. This is shown in Figure 4a, which plots the distribution of firms over the firm size ladder in the baseline model for 1987-89. The figure also displays the corresponding distribution for 2015-17. The distribution of firms over the job ladder is further skewed to the right between the two time periods. In the first experiment, I, therefore, hold all parameters, including the number of firms, constant to the baseline calibration in Table 1 and only change the distribution of firms over the job ladder, $\{n_i / \sum_{i=1}^{N} n_i\}_i$, from the blue bars in 1987-89 to the green ones in 2015-17 shown in Figure 4a. In this experiment, the aggregate employment-weighted number of firms in the model remains the same between 1985-90 and 2012-17.

II. Decreasing firms per worker uniformly over the job ladder: Apart from the changing distribution of firms over the job ladder, the US economy also observed an aggregate decline, of 13.1 percent, in the number of firms per worker between 1985-2017. This decrease is shown in Figure 1, which plots the time series of firms per worker for the US economy. In the next experiment, I simulate a symmetric decrease in the firms per worker in the model. This is done by decreasing the number of firms, n_i, at each productivity level, and within each market, by 13.1 percent. This causes the employment-weighted number of firms in the model to decrease to 231 in 2012-17. I hold all other parameters of the model, including the distribution of firms over the job ladder and the number of workers, fixed to their baseline values in Table 1.

III. Changing firms per worker asymmetrically over the job ladder: Experiment II assumed that the decrease in firms per worker observed in the US occurred uniformly across the productivity distribution; however, there is no a priori reason to assume the decrease was symmetric. To examine whether different points of the job ladder experienced differential changes in firms per worker over time, I again approximate the job ladder by the conditional firm size ladder. Figure 4b plots changes in the employment-weighted average firms per worker between 1987-89 and 2015-17 for the five firm size bins from the BDS, conditional on firm age and sector. The figure points to a scenario far from a constant change in firms over the job ladder. Between the two time periods, small-sized firms saw an increase in the average number of firms per worker, whereas most of the aggregate decline resulted from large-sized firms. This happened because the growth rate of employees outpaced the growth rate of firms among the largest firm-size classes. In other words, the firm size distribution became increasingly dispersed over time.[22] In the next experiment, I utilize the asymmetric nature of shifts in firms per worker across different firm size classes. Specifically, I vary differentially the number of firms, n_i, in each

[22] I discuss this in more detail in Section 4.1.

tier of the job ladder by the same extent to which it changed in the corresponding size class in figure 4b. This translates to an increase in n_1 by 7.2 percent, a decrease in n_5 by 31.8 percent, and so on across all markets of the model. In this experiment, the aggregate employment-weighted number of firms increases in the model from 266 in 1985-90 to 274 in 2012-17.

IV. Changing firms per worker uniformly along with changing distribution of firms over the job ladder: This experiment combines experiments I and II above. In particular, holding all parameters constant, I shift the distribution of firms over the job ladder *and* decrease the number of firms uniformly by 13.1 percent across all tiers of the job ladder. This results in a decrease in the aggregate employment-weighted number of firms by 13.1 percent over the two time periods, along with a shift in the distribution of firms to the left, as shown in Figure 4a.

V. Changing firms per worker asymmetrically along with changing distribution of firms over the job ladder: The benchmark experiment combines experiments I and III above. Holding all parameters constant, I shift the distribution of firms over the job ladder *and* decrease the number of firms differentially over the job ladder. This increases the aggregate employment-weighted number of firms from 266 in 1985-90 to 275 in 2012-17. This change in firms per worker comes with a shift in the distribution of firms to the left, as shown in Figure 4b.

Table 3 reports the actual changes in EE transitions rate and Wages/Productivity observed in the data and the model implied to the changing number of firms across the various experiments described above. Panel (a) compares the average EE transitions rate and the real hourly compensation/real hourly output for the US economy in 1985-90 and 2012-17. For both periods, the long-run averages of the two moments have been computed from the CPS and BLS, respectively.[23]

Panel (b) shows the response of the model's outcomes to each of the experiments. The first experiment simulates the change in firm distribution over the job ladder shown in Figure 4a. The model can account for about 14 percent of the decrease in EE rate and a small fraction of the decrease in wages. In the second experiment, decreasing the firms per worker uniformly at each productivity level results in a similar decline in EE transitions of 2.7 percent, accounting for about 14 percent of the overall decrease over the two periods. Wages/productivity decreased by 0.3 percent, accounting for about

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

three percent of the overall decrease in the data. In the third experiment, simulating a disproportionate change in the number of firms in the model corresponding to Figure 4b exacerbates the decline in the two moments. The model now explains about a fourth of the overall decline in EE transitions and a tenth in wages relative to productivity. The benchmark experiment V combines a disproportionate decrease in firms with a shift in the distribution of firms, almost doubling the decrease in the two outcomes. The model captures approximately two-thirds of the decline in EE transitions and around one-fifth of the decline in wages/productivity. This decline can be attributed to a shift in the firm share to the left, along with a decrease in the number of firms per worker at the top of the job ladder by almost a third. As a result, the already large firms at the top of the job ladder experience further increases in size, contributing to the overall decline in EE transitions and wages/productivity.

This section showed the qualitative and quantitative predictions of the model when the number of firms varies, holding the number of workers and all other parameters fixed. The comparative statics captured the model response of a decline in EE transitions and wages/productivity in response to decreasing competition. In terms of magnitudes, the model can account for 64 percent of the decline in EE transitions and 19 percent of the decrease in wages observed in the US between 1985-2017. These findings are based on the benchmark experiment, which simulates a shift in the firm distribution and differential changes in firms per worker at various points along the productivity distribution.

The model presented in the previous section relies on the finite nature of firms as a key factor contributing to their market power, which leads to significant non-linearities in the model outcomes when the number of firms changes. From an empirical perspective, this translates into variations in the number of employing firms within a labor market given a specific number of workers.

The model predicts that markets with a higher number of firms would result in more outside options for workers. More outside options have twofold implications for employed workers. First, more chances for workers to quit their firms, resulting in a high rate of job-to-job transitions. Second, increased efforts of firms to retain workers result in higher average wages. In the next section, I empirically examine these model predictions and provide suggestive evidence of the model's implications.

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

	EE transitions Rate (%)	Wages/Productivity
	(a) Data	
1985 - 1990	2.83	1.00
2012 - 2017	2.29	0.90
Actual change, %	-18.9	-9.76
	(b) Model	
I. Changing distribution of firms over the job ladder		
Model change, %	-2.62	-0.30
Explained by model, %	13.8	3.09
II. 13.1 percent symmetric decrease in FPW		
Model change, %	-2.67	-0.31
Explained by model, %	14.1	3.19
III. Asymmetric change in FPW		
Model change, %	-7.06	-0.79
Explained by model, %	37.4	8.07
IV. Combining I & II:		
Changing dist of firms & symmetric change in FPW		
Model change, %	-5.36	-0.64
Explained by model, %	28.3	6.56
V. Combining I & III:		
Changing dist of firms & asymmetric change in FPW		
Model change, %	-12.1	-1.81
Explained by model, %	64.0	18.6

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

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

In this section, I first document empirical trends in the model-relevant measure of employer competition for workers − the number of firms[24] in a labor market normalized by the number of workers.[25] As the number of firms and workers in the US economy has trended upward over the last several decades, I use the ratio of the two as a measure of labor market competition. I document evidence of a persistent and long-run decline in the number of firms per worker in the US, starting from the early 1980s. I show that this decline is pervasive across two-digit industrial sectors, states, and sector-state pairs and, therefore, not a consequence of the compositional changes that have taken place over the same period in the US economy.

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

The empirical evidence on the model-relevant measure of competition and outcomes described below uses data from several sources that are outlined in Appendix B.1.

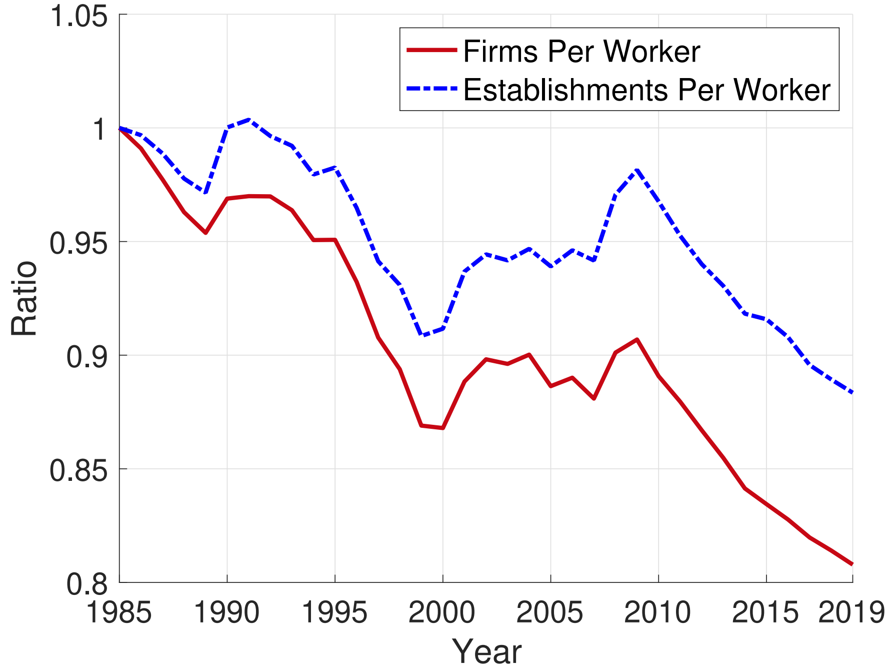
4.1 Evolution of Firms per Worker in the US Economy

I first focus on the number of firms, establishments, and workers for the aggregate US economy. Figure 5 plots trends in firms- and establishments- per worker from 1985-2019, with both ratios normalized to one at the beginning of the sample. Two observations are immediately apparent. First, both ratios experienced a long-run decline over the sample period, with firms per worker recording a steeper decline (19.2 percent) than establishments per worker (11.7 percent). While both ratios were relatively stable through the mid-80s, they started experiencing a decline by the early 90s, which became more

[24]More precisely, the empirical counterpart of the measure of competition in the model is the number of hiring firms. This measure is unavailable over a long time horizon for the US economy. I proxy for this measure by the number of firms (i.e., employer firms with a size greater than zero and excluding non-employee firms) available from the late 1970s.

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

Figure 5: 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 1985-2019 using the Business Dynamics Statistics. Both ratios are normalized to 1 at the beginning of the sample.

pronounced through the late 90s. The 2000s saw a mild recovery, following a sharp decline in the years post the Great Recession.[26] Second, the declines in firms per worker were especially sharp in periods of economic boom, suggesting that growth in employers failed to keep pace with the growth in employees. In the analysis to follow, I focus on firms rather than establishments, as I am interested in the changing number of employers rather than the number of work locations of existing employers.

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

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

Table 4: Firms per Worker by sector and time-period, 1985-2017

	1985-1990	**1995-2000**	**2012-2017**
Utilities (22)	0.008	0.010	0.010
Construction (23)	0.099	0.099	0.095
Manufacturing (31-33)	0.018	0.019	0.022
Wholesale Trade (42)	0.065	0.061	0.051
Retail Trade (44-45)	0.061	0.049	0.039
Trans & Warehousing (48-49)	0.038	0.037	0.036
Information (51)	0.021	0.022	0.022
Financial Activities (52-53)	0.081	0.077	0.079
Prof & business serv (54-56)	0.052	0.045	0.039
Edu & health (61-62)	0.034	0.030	0.027
Arts & Accomodation (71-72)	0.052	0.044	0.040
Other serv (81)	0.128	0.120	0.118

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.

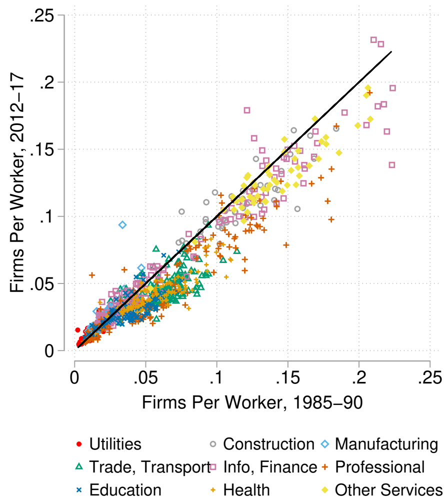
compositional changes that have taken place over the sample period in driving the aggregate trend, I examine changes in firms per worker within sectors, regions, and sector-by-region cells.

Table 4 reports long-run averages of firms per worker within sectors, or two-digit NAICS industries, over five-year horizons. A few observations are noteworthy. First, the table shows that the shrinking sectors of the economy, such as Manufacturing and Utilities, had the lowest number of firms per worker in the 80s. They were the only sectors that saw an increase in the ratio over time. A closer inspection of the trends in the levels of firms and workers plotted in Figure A2 reveals that the decline in firms could not keep pace with labor reallocating away from these sectors. As a result, these sectors experienced an overall increase in the firms per worker over the sample period.

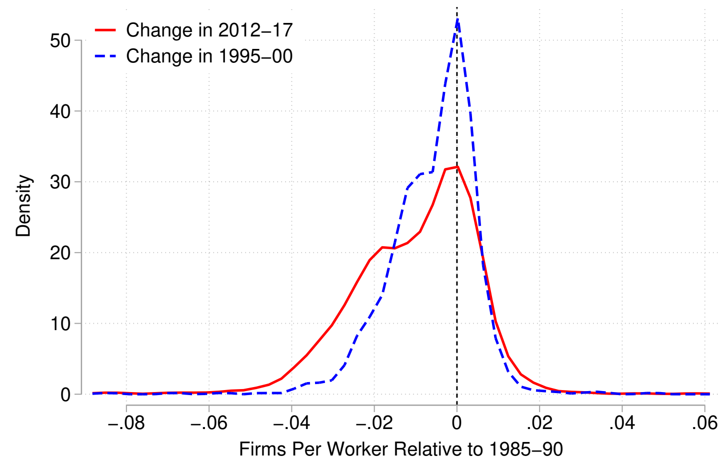
Next, Service sectors and Wholesale and Retail trade, which have grown over the last three decades, have experienced a decline in firms, even as workers have increased. This led to an overall decrease in firms per worker. For the remaining services sectors, the number of firms increased but did not keep pace with the increase in employment, leading to an overall decline in the ratio. Overall, all services sectors of the economy experienced a drop in the firm-to-worker ratio, except Information and Finance, which did not experience much change. I conclude that the aggregate decline in Figure 5 was not a result of compositional changes across sectors over the same period. Table 4 shows the opposite: sectors with the highest firms per worker in the 1980s US economy have

Figure 6: Firms per Worker in state-sector pairs

(a) Firms per Worker, 1985-90 and 2015-17



(b) Distribution of Changes in Firms per Worker, 1984-2017



Notes: Panel (a) plots the density of long-run averages of firms per worker across state × two-digit NAICS sector pairs for three time-periods. Panel (b) plots the change in density of each time period of Panel (a) relative to 1885-90 (denoted by the black dashed line at zero). The distributions are truncated at -0.1 and 0.05. Both panels use data for the US economy from the Business Dynamics Statistics.

expanded, while those with the lowest firms per worker have contracted. The aggregate decline in firms per worker was also not a result of shifting employment composition across different regions. Figure A1 plots the firms to worker ratio for all states over the sample period and shows that the decline is pervasive across all states.

Figure 6, Panel (a) shows a scatter plot of firms per worker for all states and sectors in the US. The x-axis denotes their long-run average for the 1985-90 period, while the y-axis reports the same for the 2012-17. Points below the 45 degrees solid black line depict those state-sector cells that recorded a decrease in firms per worker over the sample. The figure shows that the decline in firms per worker has been pervasive across all states and sectors of the US. To further understand the evolution of the ratio within both states and sectors, Panel (b) plots the distributions of long-run averages of firms per worker across state-by-sector cells, expressed in terms of changes relative to their counterparts in 1985-90, denoted by the vertical line at zero. The figure shows that the mass on negative values has increased – and that on positive values has declined – in each subsequent sub-period from 1985-90. Approximately 73% of the state-by-sector cells experienced a decline in firms per worker in 2012-17 relative to 1985-90.

4.1.1 Firms Per Worker and Concentration Indices

How do firms per worker compare to other measures of firm competition? Figure 7 plots the Herfindahl–Hirschman Index (HHI) of employment concentration for several sectors of the economy (Autor et al. 2020) on the left axis, along with their firms per worker on the right axis. Both measures are computed by taking weighted averages of the corresponding ratios at the 4-digit industry level. The HHI takes each sector's sales/revenue share as weight, whereas firms per worker use the employment-based weights. The figure shows a clear negative relationship between the two measures for three major super-sectors in the US: Manufacturing, Services, and Trade. Similar trends are also observed in the correlation of firms per worker, and the employment shares of the largest firms across industries, also reported in Autor et al. (2020) and shown in Figure A3.

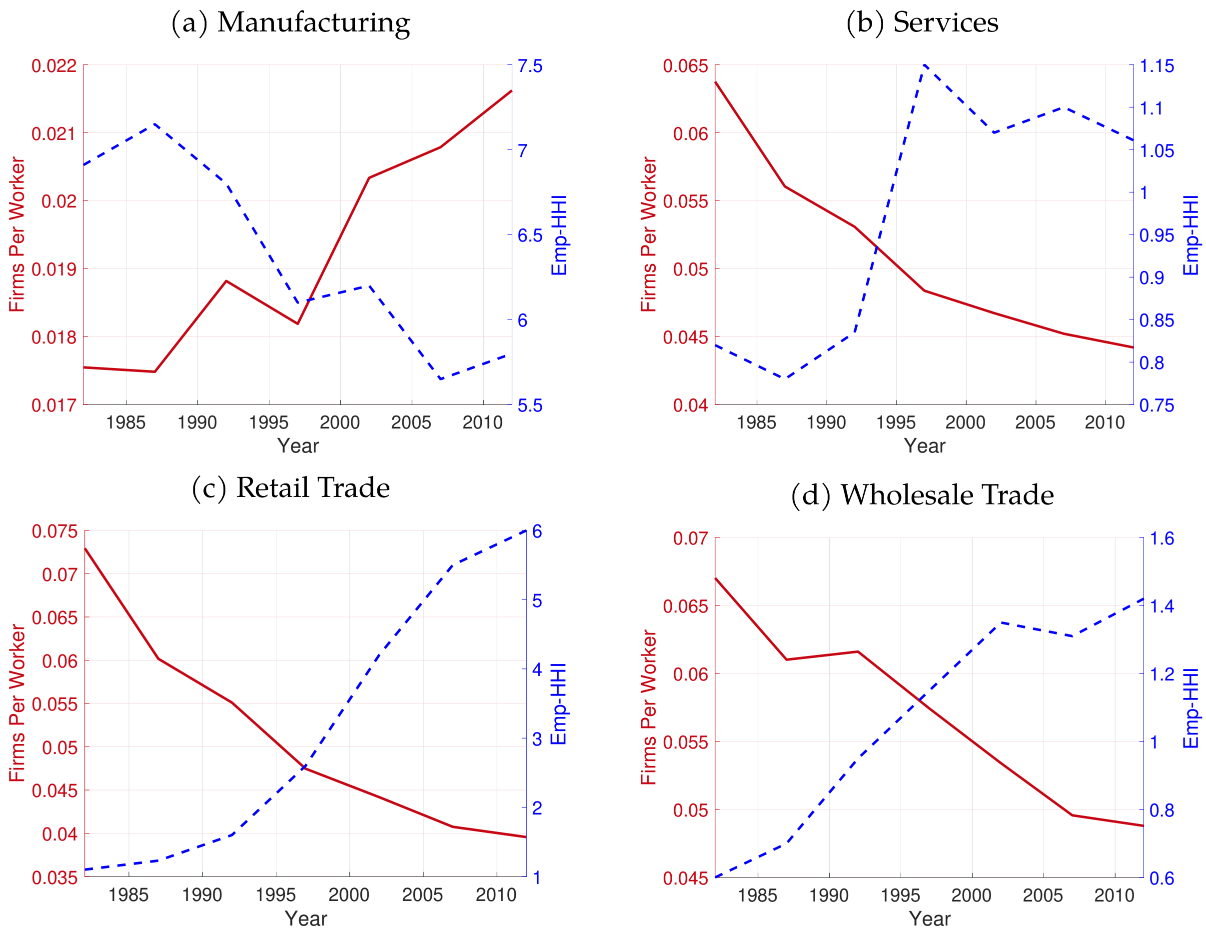
Next, Figure 8, Panel (a) plots firms per worker and sales-based HHI across all six-digit industries in the Economic Census of 2017. The relationship between the two measures is negative and robust: a one percent increase in firms per worker is associated with a 0.75 percent decrease increase in sales-based HHI. Panel (b) compares firms per worker with the employment share of the four largest firms across six-digit industries and finds a strong negative relationship.

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

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

The model presented in the last section predicts that firms per worker vary positively with (1) job-to-job transitions, (2) wages/productivity, and (3) wage growth of job stayers and negatively with (4) wage growth of job switchers. In this section, I test the model's implications pertaining to these moments using cross-sectional data. Appendix Figure A4 shows that scatter plots of raw data summarizing these relationships are consistent with the model's predictions. Panel A4a plots the average EE transitions rate and firms per worker of US state-sector pairs in 2012-17 and shows that sub-markets with higher

Figure 7: Employment-based HHI from Autor et al. (2020) and Firms Per Worker

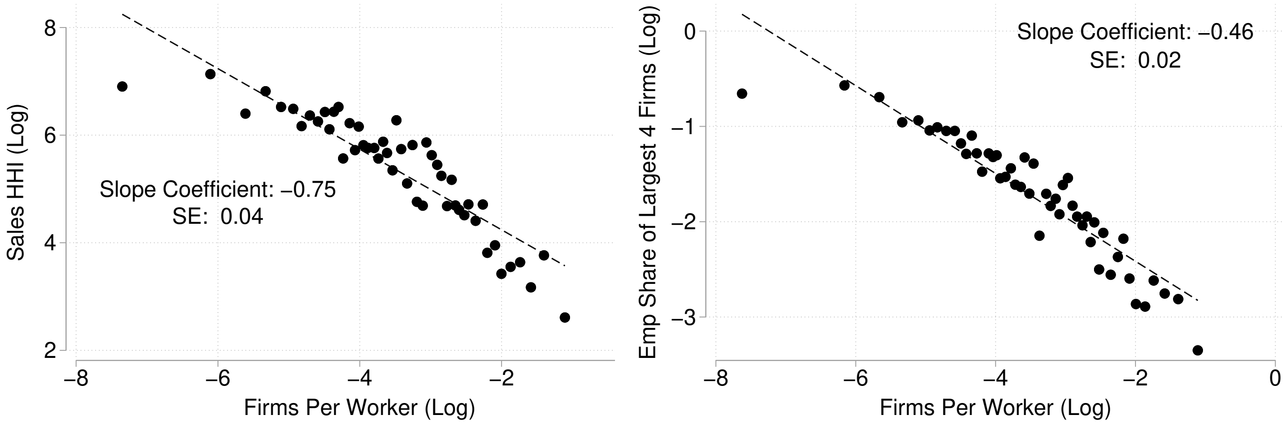


Notes: This figure displays the employment-based average HHI (Autor et al. 2020) and Firms per Worker within four-digit industries. Both indices are averaged across all four-digit industries to arrive at sector aggregates. The HHI and firms per worker, respectively, weigh industries by their share of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

firms per worker also had a higher EE transitions rate. Panel A4b plots the payroll share of value added with the firms per worker across industries in 2012-17 and shows a positive relationship between the two. Panels A4c and A4d show binned scatter plots of, respectively, individual wage growth across 12-month job spells with the same employer, and wage growth associated with EE transitions plotted against the firms per worker belonging to the state and sector of the individual between 1996-2000. Job stayers in markets with higher firms per worker experienced higher annual wage growth, and job switchers who moved from markets with higher firms per worker experienced lower wage growth. In the following sections, I explore these relationships formally in the data.

Figure 8: Sales-based HHI, Employment Concentration and Firms Per Worker

(a) Sales-based HHI and FPW (b) Employment-share of Top 4 firms and FPW



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

4.2.1 Firms Per Worker and EE Transitions

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

$$log(EE\ Rate)_{jmt} = \beta_1 log(Firms\ Per\ Worker)_{jmt} + \beta_2 X_{jmt} + \alpha_{jt} + \alpha_{mt} + \epsilon_{jmt} \qquad (15)$$

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

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

	Dependent Variable: Log EE Rate		
	(1)	(2)	(3)
Log Firms per Worker	0.056***	0.084***	0.106***
	(0.021)	(0.017)	(0.017)
Controls	N	Y	Y
Metro-Year FE	N	N	Y
Industry-Year FE	N	N	Y
N	113267	69867	69819
R^2	0.91	0.94	0.96

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

metropolitan areas.[27] All standard errors are clustered at the metropolitan area-by-sector level and sub-markets are employment-weighted.

Table 5 columns (1)-(3) report the coefficient on log firms per worker from estimating different specifications of equation 15, where the dependent variable is the EE separations rate. Overall, the number of firms per worker is positively related to the EE transitions rate. When the specification is run with only MSA, year, and sector fixed effects (specification 1), a one-log point increase in firms per worker is associated with an increase of about 0.06 log points in the EE transitions rate. Further, controls for demographic composition of workers and firms in the labor market (specification 2) increases the correlation between the two variables to 0.08. Additionally, introducing sector-year and MSA-year fixed effects (specification 3) keeps the coefficient increases the correlation to 0.11. Overall, table 5 suggests EE transitions rates are higher in markets, defined as MSA-sector pairs, with more firms per worker.[28]

To sum, this section shows a positive association between firms per worker and job-to-

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

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

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

	Dependent Var.: Log Payroll Share of Value Added		
	(1)	(2)	(3)
Log Firms per Worker	0.092***	0.075***	0.076***
	(0.014)	(0.015)	(0.017)
Year FE	N	Y	Y
2-digit Industry FE	N	Y	Y
Industry-Year FE	N	N	Y
N	1601	1601	1522
R^2	0.03	0.21	0.18

Notes: This table displays regressions of log payroll share of value added on the log number of firms per worker in each column. Column (1) shows the raw correlation coefficient. Columns (2)-(3) successively add controls for year, 11 sectors, and year-sector fixed effects. The sample is at the year-industry level from 1987-2019 for 58 industries defined at the two- and three-digit NAICS level. Robust SEs in parenthesis. Sample trimmed at 5 and 95 percentiles and Agriculture and Mining sectors have been removed. Source: Bureau of Economic Analysis, 1987-2019. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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

4.2.2 Firms Per Worker and Payroll Share of Value Added

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

In this section, I document a positive relation between firms per worker and the compensation to payroll employees as a fraction of the gross value added. This ratio can be expressed as:

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

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

$$log(Wages/Productivity)_{jkt} = \beta \cdot log(Firms\ Per\ Worker)_{jkt} + \alpha_k + \alpha_t + \epsilon_{jkt} \tag{16}$$

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

Table 6 reports the elasticity of wages/productivity to firms per worker. Specification (1) shows the raw correlation coefficient, whereas specifications (2)-(3) successively control for a year, eleven 2-digit sectors, and year-sector fixed effects. The variation in the last column utilizes differences across disaggregated industries and industry-years, within a broader sector and year. It also controls for time-varying characteristics of the sector to which the industries belong. The regression coefficient remains positive across all specifications, showing that the number of firms per worker positively relates to wages/productivity. Specification (1) shows that a one-log point increase in firms per worker is associated with an increase of about 0.09 log points in the payroll share. Further, controlling for fixed differences across sectors and year-by-sectors decreases the correlation between the two variables to 0.08 in specifications (3) and (4).

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

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

The model presented in the last section predicts that wage growth associated with EE transitions is negatively related, while that associated with continuous job spells is positively related to the number of firms per worker. As the workers' labor market becomes populated with an increasing number of firms, they become more likely to receive outside offers through on-the-job search. In such a setting, workers receiving more offers on the job realize higher levels of wages (and potentially max out on wages in the model) as job stayers. Thus, when they transition from one job to another, they realize lower gains associated with those moves. This leads wage growth realized through job switches to be negatively related to firms per worker. In this section, I document these model-implied relationships in the 1996 panel data from the SIPP. The reduced form specification is the following:

$$\Delta log(w)^k_{ijst} = \beta_1 log(\textit{Firms Per Worker})_{jst} + \beta_2 X_{it} + \alpha_j + \alpha_s + \alpha_t + \epsilon_{ijst} \tag{17}$$

where $\Delta log(w)^k_{ijst}$ is the change in the log of (1) wages paid to hourly workers, and (2) earnings paid to non-hourly workers, both deflated by the Consumer Price Index-Urban. The subscripts i denotes individual, t, the calendar-month, j, the sector, s, the state, and superscript $k \in \{\text{Stayer}, \text{Switcher}\}$ distinguishes between a job-switcher and a job stayer continuously employed over a year. $\Delta log(w)$ is computed month-over-month for job switchers, and over a year for job-stayers. The sample is restricted to workers making EE transitions or completing at least one 12-month employment spell with the same employer. The primary explanatory variable, $log(\textit{Firms Per Worker})$ is the firms per worker defined for state-s and two-digit sector-j.[29] X_{it} is a vector of worker and job-specific characteristics, including dummies for age, squared age, education, race, and gender of the worker, and whether the employer is in the public sector, the occupation and unionization status of the job to control for composition effects. α_j, α_s and α_t denote sector, state and calendar-month effects. For job switchers, the right-hand side variables are associated with the job at month $t-1$, i.e., pertaining to the job that the worker is separating from while making the EE transition. The results remain robust if I instead benchmark the right-hand side variables to the job the worker is getting hired to. The regressions for job stayers additionally include person-fixed effects. I use person-weights, restrict the sample to 16-65-year-old individuals, and cluster standard errors at the state-by-sector level.

Table 7 Panel (a) presents the regression results for job switchers. Columns (1) and (2) show that a ten percent increase in firm per worker is associated with a 0.1 percentage point decrease in wage growth and a 0.3 percentage point decrease in the earnings growth associated with job-to-job transitions. Panel(b) reports the results for job stayers. Columns (3) and (4) show that a ten percent increase in firms per worker is associated with a 0.08 percentage point increase in earnings growth of job stayers and a negligible increase in the wage growth of hourly workers. Overall, I find support for the idea that workers in markets with higher firms per worker realize a smaller wage growth as job switchers and higher ones as stayers.

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

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

	(a) Wage Growth | Job Switchers		(b) Wage Growth | Job Stayers	
	Hourly Worker (1)	Monthly Earnings (2)	Hourly Wages (3)	Monthly Earnings (4)
Log (Firms Per Worker)	-0.0112**	-0.0291**	0.0006	0.0084**
	(0.005)	(0.014)	(0.001)	(0.004)
State FE	✓	✓	✓	✓
2-digit Industry FE	✓	✓	✓	✓
Calendar month FE	✓	✓	✓	✓
Observations	18113	7918	26845	20010
R^2	0.02	0.04	0.42	0.34

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

5 Conclusion

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

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

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

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

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A Model Appendix

A.1 Nash Bargaining

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

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

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

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

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

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

which simplifies to equation 3:

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

■

A.2 Solution Algorithm

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

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

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

A.3 Wage Function

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

Start with the worker value function in equation 5 and plugging in the Nash Bargaining equation:

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

The value function of the worker can also be expressed as the following, combining equations (3) and (10):

$$\begin{aligned}(\gamma+\delta)W_{ij} &= (1-\alpha)\theta_j + \alpha\theta_i + \delta V_u \\ &+ (1-\alpha)\lambda_1 \Bigg(\sum_{x=j+1}^{N} \Big((1-\alpha)V_{jx} + \alpha V_x - V_{ji} \Big) n_x f_x - \alpha(V_i - V_{ij}) f_i + (V_j - V_{ji})(n_j - 1) f_j \Bigg) \\ &+ \alpha\lambda_1 \sum_{x=i+1}^{N} \Big((1-\alpha)V_{ix} + \alpha V_x - V_i \Big) n_x f_x\end{aligned} \tag{A.2}$$

Combining equations (A.1) and (A.2), the wage function can be expressed as:

$$
\begin{aligned}
\omega_{ij} =&(1-\alpha)\theta_j + \alpha\theta_i \\
&+ \lambda_1 \Bigg\{ (1-\alpha)\Bigg(\sum_{x=j+1}^{N} \Big((1-\alpha)V_{jx} + \alpha V_x - V_{ji} \Big) n_x f_x - \alpha (V_i - V_{ji}) f_i + (V_j - V_{ji})(n_j - 1) f_j \Bigg) \\
&+ \alpha \sum_{x=i+1}^{N} \Big((1-\alpha)V_{ix} + \alpha V_x - V_i \Big) n_x f_x - \sum_{x=i+1}^{N} \Big((1-\alpha)V_{ix} + \alpha V_x - W_{ij} \Big) n_x f_x \\
&- \sum_{x=j+1}^{i-1} \Big((1-\alpha)V_{xi} + \alpha V_i - W_{ij} \Big) n_x f_x - \Big(V_i - W_{ij} \Big)(n_i - 1) f_i \Bigg\}
\end{aligned}
\tag{A.3}
$$

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

A.4 Equilibrium Flows in the Labor Market

In this section, I describe the equilibrium flows of unemployed and employed workers in the labor market. Let u denote the stock of the unemployed and let $e(\theta_i, \theta_j)$ denote the stock of workers employed at an individual firm with productivity θ_i and outside option θ_j.

The size of such a firm is given by $E(\theta_i) = \sum_{j=u}^{i} e(\theta_i, \theta_j)$. Therefore, the total size of all firms at productivity level θ_i is $n_i E(\theta_i)$. Normalizing the total mass of workers to 1, the total employment can be expressed as $1 - u = \sum_{i=u+1}^{N} n_i E(\theta_i)$.

The equation for the law of motion of unemployment is:

$$
\delta(1-u) = u\lambda_0 \sum_{x=u+1}^{N} n_x f(\theta_x) \tag{A.4}
$$

On the left-hand side, it represents the inflows to unemployment, which is the stock of employed workers who separate from their jobs. On the right-hand side, it represents the outflows from unemployment, which is the stock of unemployed workers who find a job with a higher productivity level than their reservation threshold.

Next, consider the law of motion of employment. The stock of workers at $e(\theta_i, \theta_j)$ with

$u < j < i$, can be expressed as:

$$\lambda_1(1-\delta)\Bigg(\underbrace{n_j f(\theta_j)\sum_{x=u}^{j-1} e(\theta_i,\theta_x)}_{Stayers^+} + \underbrace{f(\theta_i) n_j E(\theta_j)}_{EE^+}\Bigg)$$
$$= e(\theta_i,\theta_j)\Bigg[\underbrace{\delta}_{EU} + (1-\delta)\lambda_1\Bigg(\underbrace{\sum_{x=i+1}^{N} n_x f(\theta_x)}_{EE^-} + \underbrace{\sum_{x=j+1}^{i-1} n_x f(\theta_x)}_{Stayers^-} + (n_i-1)f(\theta_i)\Bigg)\Bigg] \tag{A.5}$$

The left-hand side of the equation includes two terms. The first term accounts for workers who stay in their current job and get promoted by receiving an offer from a more productive firm at productivity level θ_j. The second term represents workers who switch jobs from any firm at productivity level θ_j to firm θ_i.

On the right-hand side, the equation accounts for workers who leave their current position at (i, j) either because they were separated to unemployed, or to move to a better firm, or get promoted to a better position within the same firm, or move to one of the peer firms at productivity level θ_i. In the latter case, workers may choose to either stay or move to the new firm.

The stock of workers at $e(\theta_i, \theta_j)$ with $j = i$, can be expressed as:

$$\lambda_1(1-\delta)\Bigg(\underbrace{f(\theta_i)(n_i-1)\cdot(1-\nu)\cdot\sum_{x=u}^{i-1} e(\theta_i,\theta_x)}_{Stayers^+} + \underbrace{f(\theta_i)\cdot\nu\cdot(n_i-1)E(\theta_i)}_{EE^+}\Bigg)$$
$$= e(\theta_i,\theta_i)\Bigg[\underbrace{\delta}_{EU} + (1-\delta)\lambda_1\Bigg(\underbrace{\sum_{x=i+1}^{N} n_x f(\theta_x)}_{EE^-} + \underbrace{(n_i-1)f(\theta_i)\nu}_{EE^-}\Bigg)\Bigg] \tag{A.6}$$

The left-hand side's first term represents workers at the same firm-θ_i, positioned below i, who receive an offer from any of the remaining firms at i and stay with a promotion. The second term is composed of all workers at the remaining firms at i who receive an offer from i and decide to leave. The right-hand side encompasses all workers who leave for either a better firm or one of the peer firms at i.

Finally, the stock of workers at $e(\theta_i, \theta_j)$ with $j = u$, can be expressed as:

$$\underbrace{u\lambda_0 f(\theta_i)}_{UE} = e(\theta_i, \theta_u)\Bigg[\underbrace{\delta}_{EU} + (1-\delta)\lambda_1\Bigg(\underbrace{\sum_{x=i+1}^{N} n_x f(\theta_x)}_{EE^-} + \underbrace{\sum_{x=u+1}^{i-1} n_x f(\theta_x)}_{Stayers^-} + (n_i - 1) f(\theta_i)\Bigg)\Bigg] \tag{A.7}$$

Combing the above equations, we can express law of motion of employment at firm-θ_i:

$$\begin{aligned}
&\underbrace{u\lambda_0 f(\theta_i)}_{UE} + \lambda_1(1-\delta)\Bigg(\underbrace{f(\theta_i)\sum_{j=u+1}^{i-1} n_j E(\theta_j)}_{EE^+} + \underbrace{f(\theta_i)\cdot\nu\cdot(n_i-1)E(\theta_i)}_{EE^+}\Bigg) \\
&\qquad = E(\theta_i)\Bigg[\underbrace{\delta}_{EU} + (1-\delta)\lambda_1\Bigg(\underbrace{\sum_{x=i+1}^{N} n_x f(\theta_x)}_{EE^-} + \underbrace{\nu(n_i-1)f(\theta_i)}_{EE^-}\Bigg)\Bigg]
\end{aligned} \tag{A.8}$$

Then we can define, EE transitions as:

$$EE^-(\theta_i) = E(\theta_i)\lambda_1(1-\delta)\Bigg(\underbrace{\sum_{x=i+1}^{N} n_x f(\theta_x)}_{\text{vertical EE}} + \underbrace{(n_i-1)f(\theta_i)\nu}_{\text{horizontal EE}}\Bigg) \tag{A.9}$$

$$EE^+(\theta_i) = \lambda_1(1-\delta)f(\theta_i)\Bigg(\underbrace{\sum_{j=u+1}^{i-1} n_j E(\theta_j)}_{\text{vertical EE}} + \underbrace{(n_i-1)E(\theta_i)\nu}_{\text{horizontal EE}}\Bigg) \tag{A.10}$$

A.5 Model: Shutting off the Retaliation Channel

In this section I describe a version of the model outlined in Section 2, with the retaliation channel shut off. The wage setting equation 3 is replaced by the following:

$$W(\theta_i, \theta_j) = V(\theta_j) + \alpha \cdot \big(V(\theta_i) - V(\theta_j)\big) \tag{A.11}$$

The worker negotiating with firm-θ_i with an outside offer from firm-$\theta_j \leq \theta_i$ is offered a wage by firm-θ_i that ensures that the value to the worker is a linear combination of her outside option, i.e., the entire match value offered by firm-θ_j and α fraction of the increment in joint value that results from matching with firm-θ_i. The outside option, $V(\theta_j)$, now contains the possibility of matching with firm-θ_i again. Thus, for any firm-θ_j, we can write the joint value to the worker and firm as:

$$(\gamma+\delta)V(\theta_j) = y(\theta_j) + \delta U + \lambda_1\Bigg\{\sum_{x=j+1}^{N}\Bigg(W(\theta_x,\theta_j) - V(\theta_j))\Bigg)n_x f(\theta_x)\Bigg\} \tag{A.12}$$

Equation A.12 replaces equation 6 in this model. In other words, the joint value of the worker and firm-θ_i is the flow value from the match output produced, and the option value of the worker searching on-the-job and matching with any firm more productive than θ_j. As the latter set includes θ_i, equations A.11 and A.12 show that firm-θ_i now competes with it's own offer that lies in the worker's outside option.

The value to the employed worker and firm remain the same, as outlined in equations 5 and 9. For the unemployed worker, the following wage setting equation replaces equation 4:

$$W(\theta_i,\theta_u) = U + \alpha\big(V(\theta_i) - U\big) \tag{A.13}$$

Equation A.13 states that an unemployed worker and firm-θ_i negotiate a wage that offers the worker a linear combination of their value from unemployment and the joint match value of firm-θ_i. The value from unemployment contains the possibility of a future offer from θ_i and the is given by equation 7.

Thus, the model can be solved block recursively combining equations A.11, A.12, A.13, and 7.

B Data Appendix

B.1 Data

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

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

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

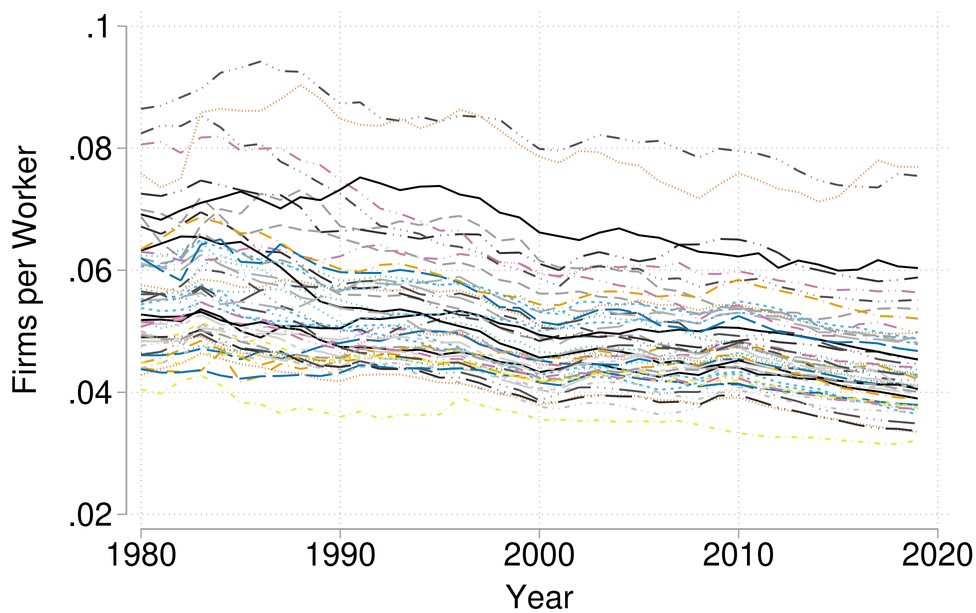
Combining the three data sources described above yields an annual panel over the sample period 2000-2018, with states entering the data at different times. The main variables of interest are measures of firms per worker, job-to-job flows, and employment composition by worker-age and education groups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

To assess the model implied behavior of wages relative to productivity, I combine data on firms per worker with the annual payroll share of gross value added. I use the data from the BLS at the disaggregated-industry level from 1987. The payroll share of value added is a measure of labor share published by the Bureau of Labor Statistics (BLS). Labor income is expressed as the sum of the compensation to employees on payroll and the compensation of the self-employed, and I focus on the former component.[30] The dataset contains a panel of about sixty industries.

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

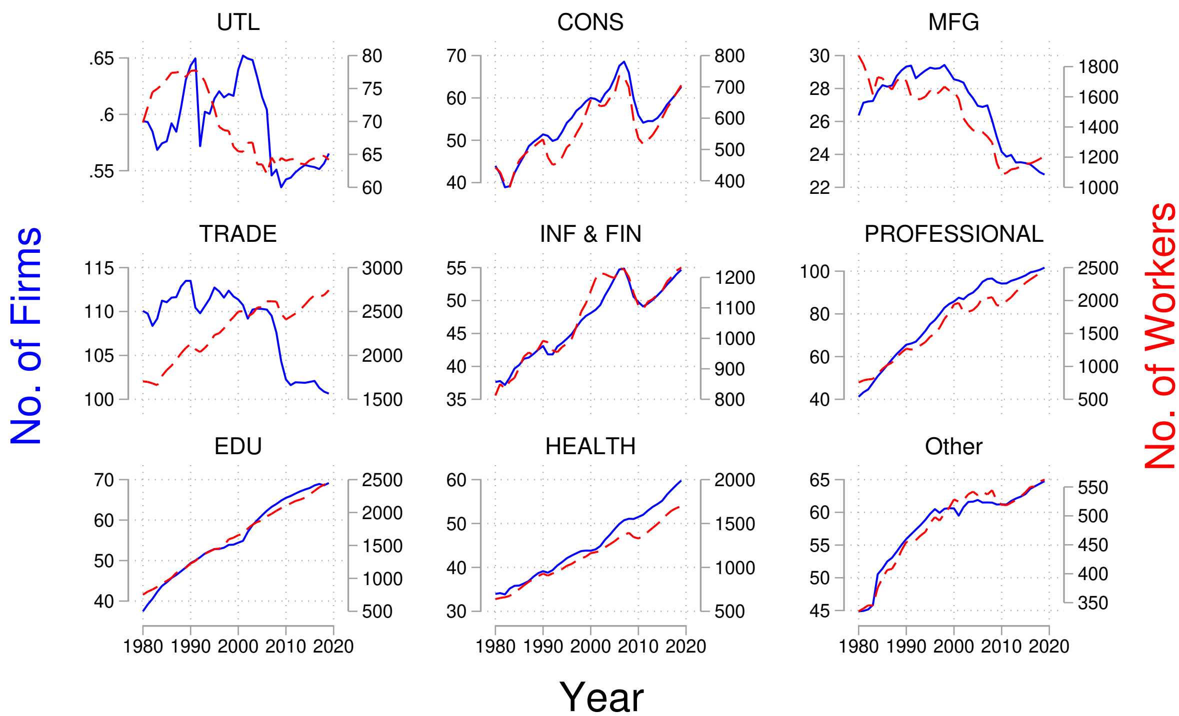
[30] Elsby et al. (2013) provide a detailed account of each component of labor share, including its measurement and constituents.

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



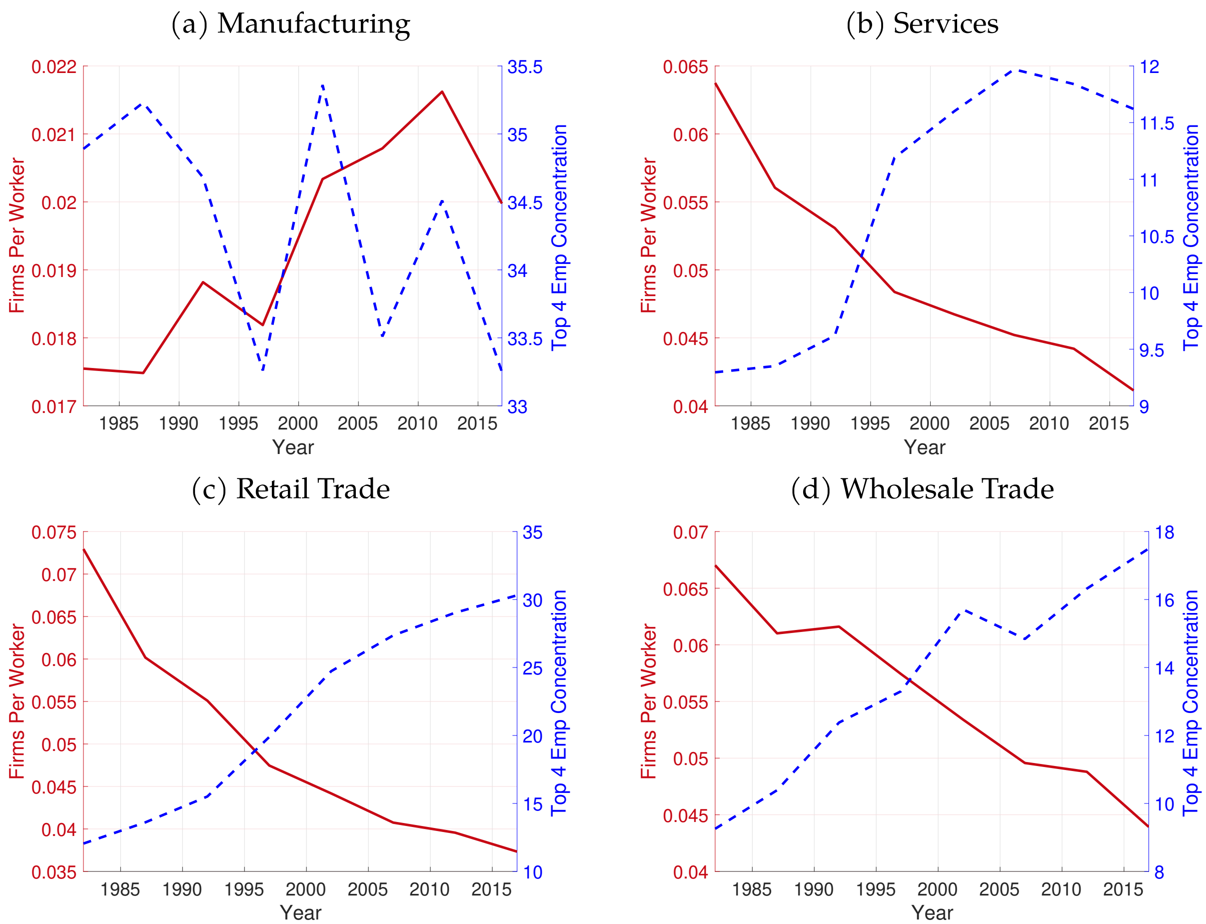
Notes: This figure shows the ratio of the number of firms to the number of workers for each state the US economy, over 1979-2018 using the Business Dynamics Statistics.

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



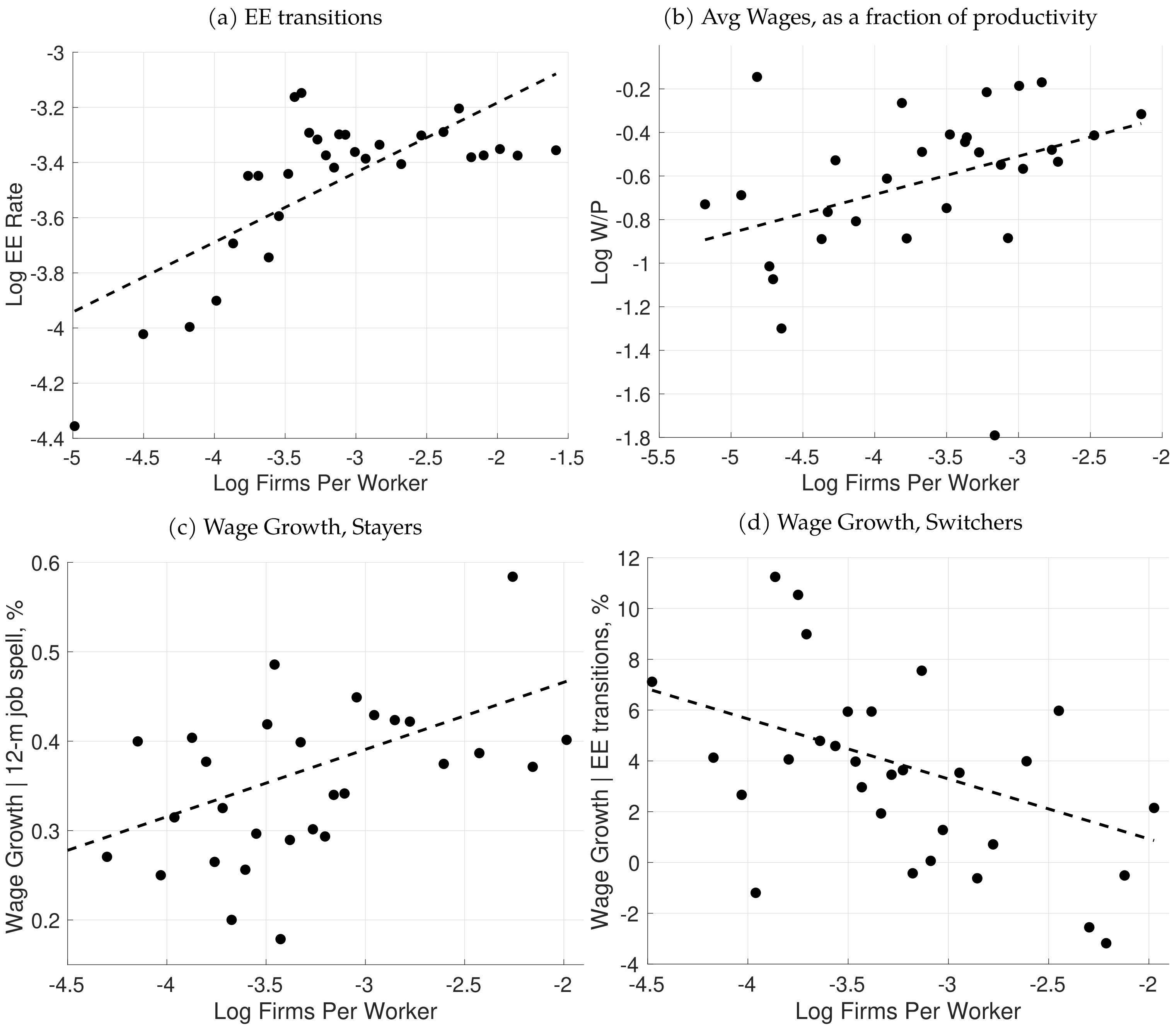
Notes: This figure plots the number of firms (left y-axis, in tens of thousands) and the number of workers (right y-axis, in tens of thousands) for each two digit NAICS sector of the US economy, over 1979-2018 using the Business Dynamics Statistics.

Figure A3: Employment share of the four largest firms from Autor et al. (2020) and Firms Per Worker



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

Figure A4: Cross-sectional Correlations in the Data



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