Declining Business Dynamism and Worker Mobility*

Carter Bryson†

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Abstract

Younger workers tend to sort into younger firms, suggesting that the decline in U.S. business dynamism differentially affected labor market outcomes over the worker life cycle. In this paper, I develop an equilibrium labor market sorting model with both on-the-job search and two-sided, life-cycle heterogeneity to quantify the career consequences of firm aging. I find that it accounts for about 45 percent of the decline in the employer switching rate and about 15 percent of the decline in the employment-to-population ratio since the 1990s. Total welfare of employed workers declines by about 0.9 percent and younger workers experience larger losses.

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†Email: carter.bryson@bea.gov. Address: U.S. Department of Commerce, Bureau of Economic Analysis, 4600 Silver Hill Road, Suitland, MD 20746

1 Introduction

During the past several decades, the United States economy has experienced a substantial decline in business dynamism. Firm entry and exit rates decreased, increasing the share of older, larger businesses. Moreover, despite broad structural shifts in economic activity over this time period, these trends were pervasive across industries and regions.[1] In this paper, I investigate the implications of declining business dynamism for labor market outcomes both in the aggregate and across older and younger generations of workers.

My analysis begins with the observation that the composition of employment within firms across worker age groups evolves over the firm life cycle. Using data from the U.S. Census Bureau's Quarterly Workforce Indicators (QWI) database, I show that the age composition of employment at younger firms is significantly skewed toward younger workers and gradually becomes more uniform as firms age. This finding is not accounted for by differences in firm size across firm age groups, is not driven by certain sectors or regions, and has remained stable over time. These sorting patterns suggest that the decline in the share of young firms in recent decades may have differentially affected the labor market outcomes of younger workers.

To assess this hypothesis and to quantify the consequences of the declining share of young firms, I build an equilibrium model of labor market sorting between heterogeneous workers and heterogeneous firms with on-the-job search. Specifically, I introduce two novel features into an otherwise standard labor market sorting model. First, I include a life cycle for both workers and firms. Second, I endogenize the firm entry process in the economy such that the equilibrium number of firms-per-worker depends on the level of entry costs and the incidence of firm exit. These features allow me to study the forces that contribute to the life-cycle sorting patterns I document in the data and to analyze the effects of firm aging on labor market outcomes across worker cohorts.

I then simulate an increase in entry costs in the model that leads to a decline in the firm entry rate and replicates the observed decline in the number of firms-per-worker in the data between 1994 and 2019.[2] Through the lens of the model, this decline in business dynamism accounts for a significant share of the decline in the employer switching rate since the 1990s both in the aggregate (Hyatt and Spletzer, 2013; Molloy et al., 2016; Fujita et al., 2024) and across the worker life cycle. In particular, younger workers experience a larger decline in employer-to-employer transitions (Baksy et al., 2024).

[1] See Decker et al. (2014), Hathaway and Litan (2014), and Pugsley and Şahin (2019) for recent evidence. These studies find broad-based declines in business formation across industries and geographic areas.

[2] Kozeniauskas (2024) finds that rising entry costs explain the majority of the decline in the firm entry rate. Bagga (2023) proposes that a lower number of firms-per-worker drove the decline in worker mobility.

In the model, both workers and firms differ by their current stage of the life cycle. Firms enter the economy at the beginning of their life cycle and post vacancies in order to hire employees. They face random shocks that cause them to close down, the incidence of which depends on how long they have been in operation. Workers enter the labor market at the beginning of their career and search for jobs. They face random shocks that separate them from their employers back into the unemployment pool. If they remain employed, they may also search on-the-job for a new employer. Employed workers earn wages that depend on their current match and stage of the life cycle.

Wages are set according to sequential auctions bargaining (Postel-Vinay and Robin, 2002) and I further assume that unemployed workers have no bargaining power when forming matches; workers hired out of unemployment receive their reservation value and firms extract the entire match surplus (Lise and Robin, 2017).[3] These assumptions deliver tractability and allow me to estimate the model to match key moments in the data.

I estimate the model in an initial steady state to match three essential dimensions of the firm life cycle.[4] First, I set higher separation rates for younger firms, matching their higher rates of turnover and lower rates of survival in the data. Second, I assume that firm productivity follows a simple, reduced-form expression over the life cycle, and estimate it to match wages by firm age. I find that older firms are larger and more productive, reflecting either selection or growth effects. Third, I allow vacancy posting costs to vary across the firm life cycle. I estimate these costs to match average firm size by firm age and find that they increase over the firm life cycle, reflecting different propensities for expansion among young versus old firms.

The model reproduces these features of the firm life cycle quite well. Additionally, though I do not target them directly in the estimation, the model matches other important features of both the firm and worker life cycle. First, the model captures the relative ranking of young versus old firms on the job ladder. In the data, older firms obtain a larger share of hires from other firms, on average, than do younger firms. The model matches this pattern qualitatively and interprets it as an increasing position in the job ladder over the life cycle. Next, in the model, as in the data, younger firms employ a higher fraction of younger workers. This is because young firms sit at the bottom of the job ladder and hire disproportionately from an unemployment pool largely composed of younger workers. Last, the model matches the declining profile of job-to-job flows across

[3] I also follow Lentz et al. (2017) and assume that firms offer workers a constant share of the match surplus until and unless the worker receives an outside offer, which delivers a closed-form solution for wages.

[4] I choose 1994 as the starting point for my analysis because of data availability reasons; wage data from the QWI are not available before the 1990s. Moreover, previous studies have argued that the negative trend in business dynamism accelerated after 2000 (Decker et al., 2014).

the worker life cycle. In the estimated model, young workers sit on lower rungs of the job ladder and are more likely to switch jobs if contacted by a firm.

With the estimated model in hand, I explore the implications of the decline in the firm entry rate for labor market outcomes. Starting from the initial steady state, I assume that the economy is hit by a shock that permanently increases the level of entry costs. I calibrate this shock to replicate the observed decline in the number of firms-per-worker in the data, and the resulting evolution of the mass of firms by firm age bin in the model matches its empirical counterpart closely. I then feed this process into the model and study the evolution of the economy along the transition path.

I find that through the lens of the model, the decline in the firm entry rate results in a decline in labor market mobility for all workers. Along the transition path of the economy, the total number of vacancies falls, leading to a decline in labor demand. Therefore, the total number of meetings between workers and firms falls, leading to a drop in the contact rate. The aggregate job finding rate declines by 3 percentage points (12%), the aggregate job-to-job switching rate declines by 0.20 percentage points (17%), and the aggregate job separation rate declines slightly. Because job finding falls more than job separation, the employment rate falls (nonemployment rate rises) by about 0.7 percentage points.

Additionally, job finding, separation, and switching rates all decline by more for younger cohorts of workers. Job finding falls by more for younger cohorts because in the estimated model, younger workers have higher search intensity. Therefore, they are more exposed to the decline in business dynamism for a given contact rate. The larger decline in job separation for younger workers is explained by a composition effect. In the initial steady state, younger workers differentially sort into younger firms, which have high separation rates. Along the transition path, as the share of young firms declines, younger workers are reallocated into jobs at older firms, which have lower separation rates. Lastly, job-to-job flows fall by more for younger workers because of their higher average search intensity and lower average job ladder position.

Taking these predictions to the data, I find that the decline in business dynamism accounts for about 45 percent of the decline in the aggregate employer switching rate and about 15 percent of the decline in the aggregate employment-to-population ratio between 1994 and 2019.[5] Notably, the decline in business dynamism also accounts for the larger decline in worker mobility among younger worker age groups (Bosler and Petrosky-Nadeau, 2016; Mercan, 2017; Baksy et al., 2024). In the model, as in the data, the aggregate decline in worker mobility is driven by larger declines among younger cohorts.

[5]The aggregate data series include only men age 25 and over to minimize the concern that changes in labor force attachment also affected these outcomes during this period.

My baseline analysis holds the worker distribution constant at the initial steady state. However, recent studies argue that demographic change drove the aggregate decline in employer switching and reallocation (Engbom, 2019; Hopenhayn et al., 2022; Karahan et al., 2024). Therefore, I conduct an additional experiment where I allow both the firm and worker distributions to evolve as in the data to analyze the combined effects of firm and worker aging. I perform a shift-share analysis to formally decompose the aggregate decline in the employer switching rate into components stemming from changes in (i) age-group-specific employer switching rates versus (ii) labor force composition. I apply this decomposition to both data from the Current Population Survey (CPS) and simulated trends from the model. I find that in both the data and the model, the former component dominates. Hence, through the lens of the model, the decline in firm entry accounts for the differential trends in employer switching across the worker life cycle that in turn drive the decline in the aggregate employer switching rate. This finding in particular provides validation for the model mechanism.

Lastly, I quantify the welfare implications of the shift in the firm age distribution to assess and unpack the mechanisms through which declining business dynamism affects workers. As the firm entry rate declines, two competing channels affect workers' labor market prospects. First, as there are fewer firms in the economy, the opportunity to match with any given firm declines. Second, as the share of older businesses, which I estimate to be more productive, increases, the average match in the economy is of higher quality. I refer to the former as the *matching channel* and to the latter as the *sorting channel*.

I find that quantitatively, the *matching channel* dominates, and employed workers experience an overall decline in welfare of about 0.9 percent. Though the employment distribution shifts toward more stable jobs at older businesses, overall employment opportunities diminish as the number of firms-per-worker falls. Similarly, though workers sort into better matches on average than in the initial steady state, average within-match wages fall. The wage setting mechanism in the model implies that with fewer firms competing to poach workers away from other firms, workers experience a deterioration in their outside options. Therefore, as the number of firms-per-worker falls, workers command a lower share of the surplus within matches, on average, and hence are paid lower wages. Moreover, as worker mobility declines, workers are more likely to remain on lower rungs of the job ladder within firms.

The welfare results across worker cohorts mirror my findings on worker mobility and wages across the life cycle. Because employment rates and wages fall by more for younger worker age groups, their welfare measures also display larger declines. Total welfare declines during the period under consideration, but the brunt of the impact is borne by younger workers. Therefore, I argue that the large decline in business dynamism in the U.S. has not only led to a deterioration of labor market prospects for all workers, but also contributed to a widening gap in outcomes between recent and past generations of labor market entrants.

Related Literature My paper contributes to several different strands of the literature that investigates the causes and consequences of the decline in business dynamism.[6] Two recent studies in particular document important empirical evidence that motivates my analysis. Both Hopenhayn et al. (2022) and Karahan et al. (2024) find that firm dynamics within cohorts of firms remained mostly stable in recent decades. Therefore, they argue that the decline in the firm entry rate primarily accounted for the changing composition of firms by firm age and drove observed aggregate trends in firm dynamics such as the firm exit rate, average firm size, and concentration. They then show that a decline in labor supply growth is consistent with these empirical patterns. My paper complements these studies by also analyzing the implications of trends in business dynamism for labor market outcomes across worker cohorts.

My study connects to several papers that consider the life-cycle dimensions of worker mobility, the job ladder, and labor market sorting. First, Topel and Ward (1992) argue that early-career "job shopping" is an important source of life-cycle wage growth. Next, Ouimet and Zarutskie (2014) document that young firms tend to hire and employ young workers in greater proportions. Last, Dinlersoz et al. (2019) find that labor market frictions specific to newly created businesses are key for generating the observed patterns of sorting between workers and firms at different stages of the life cycle. In my study, I develop a model that can capture these cross-sectional patterns and explore their implications for workers in response to long-run changes in the economy.

Next, this paper builds on work in Postel-Vinay and Robin (2002) and Lise and Robin (2017), who develop models of two-sided heterogeneity and labor market sorting. In these models, worker types differ by fixed skill or ability and firm types differ by fixed productivity or technology. In contrast to these papers, I allow firms and workers to differ not by skill or productivity, but by age, which evolves over the life cycle. This allows me not only to capture the life-cycle dimensions of worker mobility and labor market sorting, but also to speak to differential changes in labor market outcomes across cohorts.

This paper is also related to recent studies that jointly consider firm dynamics and on-the-job search. Engbom (2019) finds that while the direct effects of labor force aging

[6] While the literature on business dynamism is too large to catalog extensively here, Decker et al. (2016) and Ackcigit and Ates (2021, 2023) provide recent overviews.

explain some portion of the decline in worker flows in the United States, the majority of the decline results from feedback effects onto the incentives to start new businesses. My results are consistent with his paper, as I show that firm aging played a direct role in the decline in worker mobility. Bilal et al. (2022) and Elsby and Gottfries (2022) build tractable models of firm dynamics with frictional labor markets, on-the-job search, and decreasing returns to scale in production. My framework incorporates a life-cycle dimension for both workers and firms, maintaining analytical tractability under a related set of assumptions on the production and vacancy posting cost functions.[7] Relative to these papers, which focus on the business cycle dimension of worker flows, I study long-term trends.

Finally, my paper relates to studies that propose explanations for the declining trend in worker mobility.[8] Cairó (2013) shows that an increase in job retraining requirements lowers labor market turnover and can explain about one-third of the decline in the job reallocation rate over the past several decades. Mercan (2017) and Pries and Rogerson (2022) propose that better ex-ante information about match quality or screening by firms of potential applicants can explain the decline in job mobility in recent decades. Relative to these papers, I propose a new channel for the decline in worker mobility through the decline in the firm entry rate. The mechanism at work in my paper is most similar to that in a recent contribution by Bagga (2023), who shows that the decline in the number of firms-per-worker can explain almost two-thirds of the decline in worker mobility in the U.S. since the 1980s. Relative to her paper, I study the life-cycle dimension of the decline in worker flows and find that declining business dynamism also accounts for the larger decline in employer-to-employer transition rates experienced by younger cohorts.

Layout The rest of the paper is structured as follows. In Section 2, I review empirical evidence that motivates my analysis. In Section 3, I present an equilibrium model of labor market sorting between workers and firms at different stages of the life cycle. Section 4 discusses the numerical implementation and estimation of the model. Section 5 explores the effects of a decline in business dynamism on the economy, compares the model's predictions to the data, and discusses welfare implications. Section 6 concludes.

[7] See the discussion in Bilal et al. (2022) on the relationship between their model and Lise and Robin (2017).

[8] Hyatt and Spletzer (2013) find that depending on the data source, hires and separations rates fell between 10 percent and 38 percent between 1998 and 2010. Molloy et al. (2016) document a clear downward trend in the pace of worker flows and of job turnover and discuss competing explanations for these trends.

2 Motivating Evidence

In this section, I present motivating evidence on trends in firm dynamics and on the age distribution of employment over the firm life cycle. First, I review recent findings that changes in the firm age distribution over the past several decades were primarily driven by changes in the firm entry margin. Then, I show evidence that the age composition of employment at younger firms is significantly more skewed toward younger workers. I describe the data sources in Appendix A and the methodology below.

2.1 Aggregate Firm Dynamics Trends

Figure 1 displays trends in various measures of firm dynamics from 1994 to 2019.[9] Over this time period, the entry rate of new firms declined, exit rates conditional on firm age were mostly stable, and the firm age distribution shifted toward older firms. Moreover, the decline in the firm entry rate was a pervasive phenomenon across markets (Decker et al., 2014; Pugsley and Şahin, 2019).[10] It was not a result of the changing industrial composition of economic activity (panel 1a). However, business dynamics conditional on firm age have remained fairly stable over this time horizon (Pugsley and Şahin, 2019; Hopenhayn et al., 2022; Karahan et al., 2024). For instance, average growth and survival rates do not display large trends within firm age groups (panel 1b).

Given the relative stability of firm dynamics conditional on firm age, changes in the entry margin predominantly drove changes in the composition of firms by firm age (panel 1c). Therefore, aggregate trends in firm exit rates, growth rates, average firm size, and concentration were primarily the result of changes in the firm age distribution, induced by a decline in the number of new startup firms created each year. Moreover, some of these aggregate trends would have reversed had the age composition of businesses in the economy remained constant during this period (Hopenhayn et al., 2022).

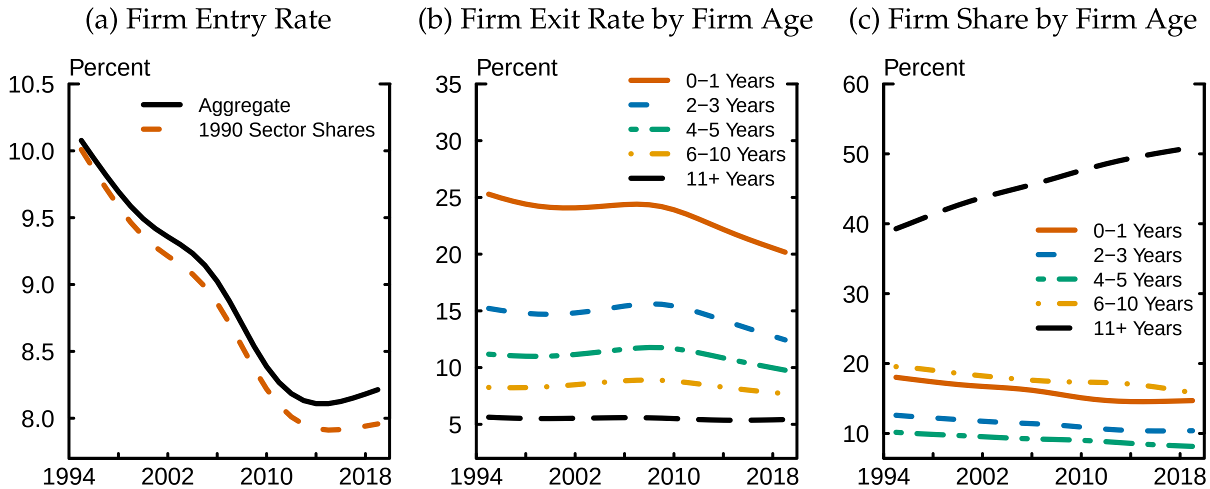
2.2 Life-Cycle Employment Sorting

Next, I examine patterns of worker and firm sorting across the life cycle using the Census Bureau's Quarterly Workforce Indicators (QWI) database and show that the composition of employment at younger firms is significantly more skewed toward younger workers. That is, younger firms tend to employ younger workers in higher proportions.

[9] I focus on trends that occurred before the onset of the COVID-19 pandemic. Recent research finds that new business applications increased dramatically during the COVID period, but analysis of the specific causes and consequences remains an open area of research (Dinlersoz et al., 2021; Decker and Haltiwanger, 2023).

[10] See Appendix B for sector specific trends in firm entry rates.

Figure 1: Trends in Firm Dynamics



Notes: The left panel shows the firm entry rate (number of age 0 firms divided by total number of firms) on aggregate and for a counterfactual scenario where firm shares by sector are held constant at their 1990 values. The center panel shows the firm exit rate (number of firm deaths divided by total number of firms) by firm age group. The right panel shows the share of firms in each firm age group. Data are from the Census Bureau's Business Dynamics Statistics (BDS) database and are HP-filtered with an annual smoothing parameter. For more details on the BDS, see Appendix A.

Figure 2 plots the composition of employment across worker age group by firm age group. For instance, the red, solid line shows that roughly 35 percent of employees at firms between 0–1 years old (startup firms) are between the ages of 25–34, while the dashed, black line shows that only about 27 percent of employees at firms 11 years or older (mature firms) are within this age range. From the figure, a striking pattern emerges. The composition of employment at younger firms is more skewed toward younger workers relative to the employment composition at older firms. In fact, the proportion of employment composed of workers less than 45 years old is declining in firm age.

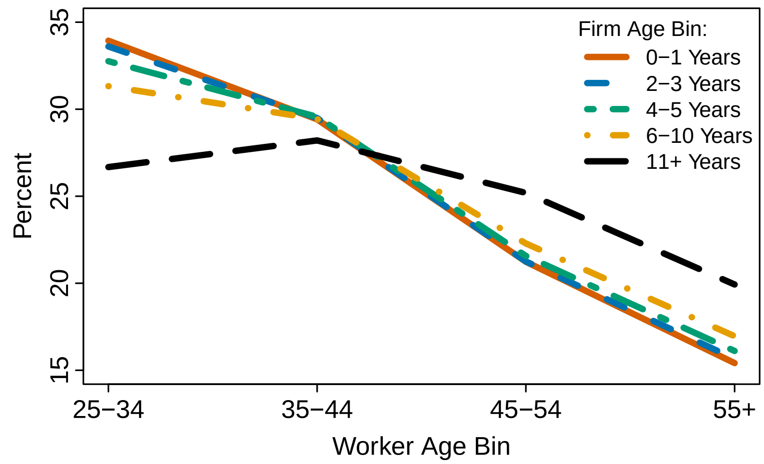
To test whether factors other than worker and firm age can account for this pattern, I estimate the following regression specification

$$\text{Frac. Age} < 45_{i,j,k,t} = \alpha + \beta \mathbb{1}\{i = \text{Firm Age 0–10 Years}\}_{j,k,t} + \mathbf{X}_{i,j,k,t} + \varepsilon_{i,j,k,t}$$

where the variable Frac. Age $< 45_{i,j,k,t}$ denotes the fraction of total employment composed of workers under the age of 45, at firms in age group i in region j and industry k during year t.[11] I regress this variable on an indicator for firm age group, so that the coefficient β captures the average difference in employment composition between young (0–10 years) and mature (11+ years) firms within a region $\times$ industry $\times$ year cell.

[11]Note that I restrict the sample to include only male workers age 25 and over.

Figure 2: Employment Distribution Across Worker Age by Firm Age



Notes: Figure shows average employment composition, in percentages, across worker age group for firms in different age groups. Data on employment by worker and firm age group are from the Census Bureau's Quarterly Workforce Indicators (QWI) database. For all series, I include only male workers and take averages over 1994–2019. For more details on the QWI, see Appendix A.

I implement this regression using data at the Metropolitan Statistical Area (MSA) by 2-digit NAICS level, and include fixed effects by MSA, sector, and year to control for the possibility that the pattern shown in Figure 2 is driven by certain regions, sectors, or time periods. I also include controls for differences in firm size across firm age groups and employment composition across different levels of educational attainment because observed sorting on age could instead reflect sorting on worker and firm characteristics that also vary across the life cycle, such as skill and productivity.

Table 1 shows the results of this exercise. The table shows that on average, young firms employ a statistically significant, higher proportion of young workers. Being a 0–10 year old firm is associated with having an employment composition of age < 45 year old workers approximately 11 percentage points higher relative to firms in the 11+ age category.[12] Moreover, this pattern does not disappear after controlling for fixed effects at various levels, firm size, or educational composition. Importantly, it is not driven by differences in firm size, as young firms tend to be smaller.[13] If anything, increases in average firm size are associated with having a *higher* proportion of young workers, and

[12]Note that these magnitudes are slightly larger than those implied by Figure 2, which uses data aggregated across regions and industries. Comparing Figure 2 with Table 1 reveals that the pattern of worker and firm life-cycle sorting is stronger at finer levels of disaggregation. Appendix B shows the employment distribution across worker age group by firm age group using the MSA $\times$ sector $\times$ year data.

[13]The literature remains ambivalent about whether firm size is a relevant characteristic for job ladder dynamics and sorting patterns (Moscarini and Postel-Vinay, 2012; Haltiwanger et al., 2018; Bilal et al., 2022).

Table 1: Worker and Firm Sorting Patterns by Firm Age

	(1)	(2)	(3)	(4)
Firm Age 0–10 Years	11.231***	11.249***	10.637***	15.049***
	(0.038)	(0.037)	(0.036)	(0.111)
Frac. Educ. $\leq$ High School				0.029***
				(0.002)
ln(Avg. Firm Size)				1.359***
				(0.032)
Firm Age 0–10 Years $\times$ ln(Avg. Firm Size)				−1.631***
				(0.046)
Year Fixed Effects	X	X	X	X
MSA Fixed Effects		X	X	X
Sector Fixed Effects			X	X
Observations	680,501	680,501	680,501	635,595
R^2	0.188	0.222	0.308	0.347

Notes: Sample includes only male workers age 25 and over for the years 1994–2019. Frac. Educ. $\leq$ High School is the fraction of a firm's workforce with less than or equal to a high school education. ln(Avg. Firm Size) is the natural logarithm of average firm size. sector fixed effects are at the 2-digit NAICS level. Standard errors in parentheses. $^{*}p \leq 0.10$;$^{**}\, p \leq 0.05$;$^{***}\, p \leq 0.01$.

this association is weaker for firms in the 0–10 year old age category.

Ouimet and Zarutskie (2014) document a similar pattern using Census microdata from 1992 to 2004. My data are at the bin-level, so I cannot control for individual worker and firm-level characteristics. However, I use the QWI to repeat the analysis above using firm size and education groups and discuss the results in Appendix C. I do not find that sorting along these dimensions masks sorting on worker and firm age, and conclude that an important life-cycle component of labor market sorting exists.

3 Model of Life-Cycle Sorting

In this section, I develop an equilibrium model of labor market sorting featuring both worker and firm heterogeneity as well as on-the-job search. In order to focus on the life-cycle sorting patterns highlighted above, I abstract from worker and firm heterogeneity other than in age. Wages are set according to a sequential auctions bargaining protocol as in Postel-Vinay and Robin (2002). Below, I elaborate on the model structure and the wage setting protocol; I relegate detailed derivations of key equations to Appendix D.

3.1 Environment

Time is discrete and extends forever. Workers and firms are heterogeneous and differ by age, where x denotes worker age and y denotes firm age. They are risk neutral and discount the future at rate $\beta = \frac{1}{1+r}$.

The mass of workers at time t is given by $\ell_t(x)$ with total mass $\mathcal{L}_t = \int \ell_t(x)\,\mathrm{d}\,x$, which is normalized to 1 in steady state. Workers enter the economy at rate η_t and retire from the labor force at rate ω_x. The mass of firms at time t is given by $m_t(y)$ with total mass $\mathcal{M}_t = \int m_t(y)\,\mathrm{d}\,y$. Firms enter the economy at rate γ_t and exit at rate ζ_y. Workers and firms age stochastically according to the Markov processes $\Pi_{x'|x}$ and $\Pi_{y'|y}$, respectively.

Workers are either employed or unemployed. Employed workers produce flow match output p_y when matched with a firm of age y. They earn flow wage $w_t(x, y)$, which is the outcome of a sequential auctions bargaining protocol outlined below.[14] Unemployed workers receive flow benefit b.

Both employed and unemployed workers search for jobs. Workers contact firms at a rate λ_t that is determined by a constant returns to scale meeting function defined below. Worker search intensity ϕ_x^i is exogenous and depends on both worker age x and employment status $i \in \{\text{employed } (e), \text{unemployed } (u)\}$. For example, an employed worker of age x contacts a firm at rate $\phi_x^e \lambda_t$.

Timing Within each period, there are two stages. At the beginning of the period, a certain fraction of workers are matched to firms and the rest are unemployed. Then, in the first stage (*separation stage*), some matches dissolve and workers in these matches enter unemployment. Next, some workers exit the labor force due to retirement and worker and firm ages are updated according to $\Pi_{x'|x}$ and $\Pi_{y'|y}$, respectively. Workers who exit the labor force are replaced by new labor market entrants, who start off unemployed.

In the second stage (*matching stage*), the total effective stock of unemployed workers (previously unemployed workers plus those newly unemployed) and the total effective stock of employed workers search for and may form matches with new firms. After the matching process resolves, the economy enters the next period.

3.2 Value Functions

Following Lise and Robin (2017), I assume that unemployed workers have zero bargaining power and are offered their reservation value if they contact a firm. Under this as-

[14] Note that equilibrium wages will depend on both worker and firm age, which I elaborate on below.

sumption, an unemployed worker's value function is given by the equation below.

$$B_t(x) = b + (1-\omega_x)\beta\, \mathrm{E}_{x'}\left[B_{t+1}(x')|x\right] \tag{1}$$

This expression states that the value of unemployment is simply the present discounted value of current and future flow unemployment payments b, which represents any per-period utility value a worker receives while unemployed.[15]

Employed workers' value $W_t(x, y, y')$ depends on their current age x, current firm y, and previous firm y', where $y' \equiv 0$ if they were hired out of unemployment. The equation for $W_t(x, y, y')$ is not specified here because it is not needed for the equilibrium computation. Instead, I proceed to define the *joint* value of an employment relationship. Let $P_t(x, y)$ denote the present discounted value of a match between a worker of age x and a firm of age y. The equation for $P_t(x, y)$ is given below.

$$\begin{aligned} P_t(x,y) = p_y + (1-\omega_x)\beta\, \mathrm{E}_{x',y'} \Big[& \big(1-(1-\delta_y)\mathbb{1}\{P_{t+1}(x',y') \geq B_{t+1}(x')\}\big) B_{t+1}(x') \\ & + (1-\delta_y)\mathbb{1}\{P_{t+1}(x',y') \geq B_{t+1}(x')\}\Big((1-\phi^e_x\lambda_{t+1})P_{t+1}(x',y') \\ & + \phi^e_x\lambda_{t+1}\int \max\{P_{t+1}(x',y'), W_{t+1}(x',y'',y')\}\frac{v_{t+1}(y'')}{V_{t+1}}\,\mathrm{d}\,y''\Big) \,|\, x,y\Big] \end{aligned}$$

In the current period, a match between a worker and a firm of age y produces p_y. If the worker does not retire, the match dissolves exogenously with probability δ_y. A match dissolves endogenously if the continuation value of the match drops below the value of the worker's outside option, $P_t(x, y) < B_t(x)$. Instead, if the match persists, the employed worker may contact a new firm of age y'' with probability $\phi^e_x\lambda_t$. If she fails to meet a new firm, the match persists with the same continuation value. However, if she meets a new firm, then the incumbent firm and the poaching firm enter into Bertrand competition over the worker's services, as in Postel-Vinay and Robin (2002).

Suppose a worker employed at a firm of age y meets a firm of age y'. There are two possible outcomes for the worker's new employer. Either the total match value is higher at the incumbent firm ($P_t(x, y) > P_t(x, y')$) and the worker remains at the incumbent firm, or the total match value is higher at the poaching firm ($P_t(x, y) < P_t(x, y')$) and the worker moves to the poaching firm. If the worker is poached, she may negotiate her wage at the poaching firm such that she receives the entire match value $P_t(x, y)$ from the incumbent

[15] In particular, b may stand for home production, leisure value, or explicit unemployment benefit payments. See Appendix D for a full derivation of the unemployed workers' value function. Though workers are technically indifferent between unemployment and employment in this setup, I follow Lise and Robin (2017) and assume that unemployed workers always accept job offers.

firm. As a result, the continuation value of the match is independent of whether the worker is poached and therefore of the employed worker value function $W_t(x, y, y')$.[16]

Joint Surplus Instead, we may write the joint worker and firm problem in terms of the joint surplus of the match. Let $S_t(x, y) \equiv P_t(x, y) - B_t(x)$ be the joint surplus at time t from an employment relationship between worker x and firm y. The surplus function determines all allocations in the economy and is given by the expression below.

$$S_t(x, y) = p_y - b + (1 - \omega_x)(1 - \delta_y)\beta \, \mathrm{E}_{x',y'} \left[\max\{S_{t+1}(x', y'), 0\} \mid x, y\right] \tag{2}$$

This equation states that the joint surplus of a match between worker x and firm y is equal to the flow output of the match net of the workers' flow value of unemployment, plus expected future surplus if the match continues. Given flow output p_y and unemployment value b, solving Equation 2 determines the surplus value of any possible match in the economy, simplifying the equilibrium computation considerably.[17]

3.3 Joint Employment Distribution

Given the surplus value $S_t(x, y)$, we next determine the employment distribution across worker and firm states. Let $u_{t-1}(x)$ and $e_{t-1}(x, y)$ denote the stocks of unemployed and employed workers, respectively, at the end of the previous period. These stocks are then updated during the *separation stage* when the economy enters period t as follows.

$$\tilde{u}_t(x') = \Pi_{x'|x}(1-\omega_x)\left(u_{t-1}(x) + \int \big(1 - (1 - \delta_y)\mathbb{1}\{S_t(x, y) \geq 0\}\big)e_{t-1}(x, y)\,\mathrm{d}\,y\right) + \eta_t \mathbb{1}\{x' = \underline{x}\}$$

$$\tilde{e}_t(x', y') = \Pi_{x'|x}\Pi_{y'|y}(1 - \omega_x)(1 - \delta_y)\mathbb{1}\{S_t(x, y) \geq 0\}e_{t-1}(x, y)$$

The first expression states that the number of middle-of-period unemployed workers of age x' is equal to any previously unemployed workers of age x plus any workers who are separated from their jobs either endogenously or exogenously, who do not retire and who transition into that age, plus new labor market entrants into the lowest worker age group $\underline{x}$. The number of new labor market entrants η_t is equal to the total number of retiring workers $\int \omega_x u_t(x) + \int \omega_x e_t(x, y)\,\mathrm{d}\,x\,\mathrm{d}\,y$ in steady state. The second expression states that

[16] This is because in the equation above, $W_{t+1}(x', y', y'') = P_{t+1}(x', y')$ as a result of Bertrand competition.

[17] Notice that neither the distribution of employment nor worker values appears in this equation, meaning that the model has the block-recursive property, as shown in Lise and Robin (2017). Block-recursivity obtains because unemployed workers have no bargaining power and the wage bargaining protocol renders the match continuation value independent of the employed worker value.

the number of middle-of-period employed workers of age x' at firms of age y' consists of workers already employed at these firms who survive job destruction and retirement.

After this initial stage, the stocks of workers $\tilde{u}_t(x)$ and $\tilde{e}_t(x,y)$ may form matches with new firms. The total effective pool of searching workers L_t is composed of these stocks scaled by their respective search intensities.

$$L_t = \int \phi^u_x \, \tilde{u}_t(x) \, \mathrm{d}\, x \; + \; \int \int \phi^e_x \, \tilde{e}_t(x,y) \, \mathrm{d}\, x \, \mathrm{d}\, y \tag{3}$$

Vacancy Posting Given L_t, $\tilde{u}_t(x)$, and $\tilde{e}_t(x,y)$, firms post vacancies to hire workers from the pool of total searchers. Define $\{x\}^* \equiv \max\{x, 0\}$ and let $J_t(y)$ be the value of meeting a worker for a firm of age y.

$$J_t(y) = \int \frac{\phi^u_x \tilde{u}_t(x)}{L_t} \{S_t(x,y)\}^* \, \mathrm{d}\, x + \int \int \frac{\phi^e_x \tilde{e}_t(x,y')}{L_t} \{S_t(x,y) - S_t(x,y')\}^* \, \mathrm{d}\, x \, \mathrm{d}\, y' \tag{4}$$

This expression has two components. Either the worker is hired from unemployment, in which case the firm offers the worker her reservation value and extracts the entire match surplus, or the worker is hired from employment, in which case the firm receives any match surplus net of the match surplus at the worker's previous firm.[18]

Firms face per-unit flow vacancy posting costs on the number of firm-level vacancies $n_t(y)$. Vacancy posting costs are governed by the function $C_y(\cdot)$, which I assume is convex and may depend on firm age y. Active firms post vacancies up to the point where the marginal cost of opening a vacancy is equal to the expected value of a filled vacancy. In equilibrium, vacancies are therefore pinned down by the condition

$$C_y{}'(n_t(y)) = \mu_t \cdot J_t(y) \tag{5}$$

where μ_t is the rate at which firms contact workers and is the outcome of the meeting process specified below. Given $J_t(y)$ and μ_t, the number of firm level vacancies by firm age $n_t(y)$ solves Equation 5. Aggregate vacancies are then given by

$$V_t = \int n_t(y) m_t(y) \, \mathrm{d}\, y = \int v_t(y) \, \mathrm{d}\, y \tag{6}$$

where $v_t(y) = n_t(y) m_t(y)$ is the total mass of vacancies posted by each firm age y.

[18]Notice that (i) if $S_t(x,y) < 0$ the match is not formed and (ii) firms can only poach from lower surplus firms.

Matching and Contact Rates Total meetings between workers and firms are governed by a Cobb–Douglas meeting function (where matching efficiency is normalized to 1).

$$\Psi(L_t, V_t) = L_t^{\alpha} V_t^{1-\alpha}$$

Hence, the contact rate for workers is $\phi_x^i \lambda_t = \phi_x^i \frac{\Psi(L_t,V_t)}{L_t}$, which depends on both labor market status and age. The contact rate for firms is $\mu_t \equiv \frac{\Psi(L_t,V_t)}{V_t}$.

Worker Flows Given surplus function $S_t(x,y)$, contact rate λ_t, vacancies V_t, and middle-of-period unemployment and employment stocks $\tilde{u}_t(x)$ and $\tilde{e}_t(x,y)$, the equations below determine end-of-period unemployment and employment stocks.

$$u_t(x) = \tilde{u}_t(x) \left[1 - \phi_x^u \lambda_t \int \frac{v_t(y)}{V_t} \mathbb{1}\{S_t(x,y) \geq 0\} \,\mathrm{d}\, y \right] \tag{7}$$

$$\begin{aligned} e_t(x,y) = \tilde{e}_t(x,y) &+ \underbrace{\phi_x^e \lambda_t \int \tilde{e}_t(x,y') \frac{v_t(y)}{V_t} \mathbb{1}\{S_t(x,y) > S_t(x,y')\} \,\mathrm{d}\, y'}_{\text{Poaching Hires}} \\ &- \underbrace{\phi_x^e \lambda_t \int \tilde{e}_t(x,y) \frac{v_t(y')}{V_t} \mathbb{1}\{S_t(x,y) < S_t(x,y')\} \,\mathrm{d}\, y'}_{\text{Poaching Separations}} \\ &+ \underbrace{\phi_x^u \lambda_t \, \tilde{u}_t(x) \, \frac{v_t(y)}{V_t} \, \mathbb{1}\{S_t(x,y) \geq 0\}}_{\text{Unemployed Hires}} \end{aligned} \tag{8}$$

Equation 7 shows that workers who fail to find jobs during the *matching stage* make up the stock of unemployed workers at the end of the period. This can be because they fail to contact a firm or because they contact a firm with negative match surplus. The terms in Equation 8 mirror the situations that can arise from the sequential auctions bargaining protocol. The stock of age x workers employed at age y firms is equal to previous employment plus any employees poached from other firms net of employees lost to other firms, plus workers hired out of unemployment.

3.4 Wage Setting

I assume that firms promise workers a constant share σ_t of the match surplus that depends on their age x, current firm y, and previous firm (previous outside offer) y', until and unless the worker receives another outside offer. In particular, for $S_t(x,y) \geq S_t(x,y')$,

$$\sigma_t \equiv \sigma_t(x,y,y') = \frac{S_t(x,y')}{S_t(x,y)} \tag{9}$$

Under this assumption, the wage equation is

$$\begin{aligned} w_t(x,y,\sigma_t) = \sigma_t p_y + (1-\sigma_t)b - (1-\omega_x)(1-\delta_y)\beta\, \mathrm{E}_{x',y'} \Big[\\ \mathbb{1}\{S_{t+1}(x',y') \geq 0\}\, \phi^e_x \lambda_{t+1} \int R_{t+1}(x',y',\sigma_{t+1},y'') \frac{v_{t+1}(y'')}{V_{t+1}} \,\mathrm{d}\, y'' \mid x,y \Big] \end{aligned} \tag{10}$$

where the term $R_t(x,y,\sigma_t,y')$ reflects the possible outcomes of the sequential auctions bargaining protocol and represents the additional surplus the worker expects to capture from future renegotiation opportunities. This equation shows that wages are a weighted average of current match output and unemployment benefit net of any expected future renegotiation opportunities and that they depend on both worker and firm age.[19]

3.5 Worker and Firm Distributions

The law of motion for the mass of workers is:

$$\ell_{t+1}(x') = \Pi_{x'|x}\big(1-\omega_x\big)\ell_t(x) + \eta_t \mathbb{1}\{x' = \underline{x}\} \tag{11}$$

where $\Pi_{x'|x}$ is the transition matrix across worker age bins, ω_x is the retirement rate for worker age x, and η_t is the rate at which workers enter the economy (into the youngest age bin $\underline{x}$). Similarly, the law of motion for the mass of firms is:

$$m_{t+1}(y') = \Pi_{y'|y}\big(1-\zeta_y\big)m_t(y) + \gamma_t \mathbb{1}\{y' = \underline{y}\} \tag{12}$$

where $\Pi_{y'|y}$ is the transition matrix across firm age bins, ζ_y is the exit rate for firm age y, and γ_t is the entry rate of firms into the youngest age bin $\underline{y}$. Given entry and exit rates, the steady state mass of firms by age $\bar{m}(y)$ is the fixed point of Equation 12. Recall that $\mathcal{L}_t = \int \ell_t(x)\,\mathrm{d}\,x$ is normalized to 1 in steady state. Hence, the interpretation of $\mathcal{M}_t \equiv \int m_t(y)\ \mathrm{d}\,y$ is the number of firms-per-worker at time t.

[19] The assumption on surplus sharing, which follows Lentz et al. (2017), is convenient because it produces a closed form solution for the wage equation. See Appendix D for the explicit expression of $R_t(x,y,\sigma_t,y')$ as well as the derivation of the wage equation.

Firm Entry Rate I assume that before entering the economy, firms must pay an entry cost χ_t. In equilibrium, the firm entry rate γ_t must be such that the expected surplus value of entering the economy and operating as a startup firm is equal to χ_t. Therefore,

$$\int f_t^e(x, \underline{y}) S(x, \underline{y}) \, \mathrm{d}\, y = \chi_t \tag{13}$$

where $f_t^e(x, \underline{y})$ denotes the employment distribution by worker age for startup firms.

4 Model Implementation and Estimation

In this section, I describe the details of the numerical implementation and estimation of the model. I estimate the model in steady state in order to match life-cycle moments in the early-1990s. Below, I outline the specific moments targeted in the estimation procedure and provide an overview of which moments in the data help to inform certain parameters.

Age Bins I define the model at the bin-level and choose the same bins as in the Census data used in Section 2. There are 4 worker age bins $\{25–34, 35–44, 45–54, 55+\}$ and 5 firm age bins $\{0–1, 2–3, 4–5, 6–10, 11+\}$, each in years. Worker ages evolve stochastically across bins according to the Markov transition matrix $\Pi_{x'|x}$ and firm ages evolve stochastically across bins according to $\Pi_{y'|y}$. The model is set at a monthly frequency, which means that in each time period, $\frac{1}{12\times10}^{th}$ of 25–34 year-old workers become 35–44 year-old workers, $\frac{1}{12\times2}^{th}$ of 0–1 year-old firms become 2–3 year-old firms, et cetera.[20] Within bins, however, workers and firms are identical. Hence, the model describes the average worker within a certain age range and the average firm within a certain age range.

Functional Form Assumptions I assume that the labor market status component of search intensity, which I denote by κ_i, and the age component, which I denote by ψ_x, enter multiplicatively, so that $\phi_x^i = \kappa_i \cdot \psi_x$. I parameterize the vacancy cost function as the iso-elastic function $C_y(n_t(y)) = c_y \frac{n_t(y)}{2}^2$ where $n_t(y)$ is the number of vacancies posted by each firm of age y at time t. Here, c_y determines the degree to which vacancy costs vary explicitly by firm age. I assume that c_y varies by firm age according to the quadratic $c_y = c_0 + c_1 y + c_2 y^2$, which allows the model to flexibly capture differences in the level of vacancy posting costs across firm ages. I assume match-level output p_y is a quadratic in firm age $p_y = p_0 + p_1 y + p_2 y^2$. Match-level output p_y is a crucial element of the match

[20] Note that workers and firms can only move up age bins, so the transition matrices contain only zeros below the diagonal. Transition matrices $\Pi_{x'|x}$ and $\Pi_{y'|y}$ are specified explicitly in Appendix E.

surplus and therefore the level of wages within matches. The assumed functional form captures differences in wages paid across firm age groups without allowing for too many degrees of freedom. I set the flow unemployment benefit b such that it is equal to some fraction b_0 of a worker's maximum attainable match output $b = b_0 \cdot \max_y\{p_y\}$.

4.1 Estimation Strategy

Table 2 shows the estimated parameters. I assume that the economy is in steady state in 1994 and estimate the model in three steps. First, I externally set a subset of parameters to commonly used values in the literature (Panel A). Next, a subset of parameters is directly informed by the data (Panel B). Last, I perform a moment matching exercise designed to target different features of the firm life cycle (Panel C).

Externally Set Parameters One period is set to one month in the model, so all rates are monthly. The discount factor is set to correspond to an annual interest rate of 5 percent. The meeting function elasticity α is set to match recent estimates of the elasticity of hires with respect to searchers (Lange and Papageorgiou, 2020). I normalize the search intensity of unemployed workers to 1 and set the search intensity of employed workers to half that of unemployed workers. This follows recent evidence from the literature on the relative time spent searching by employed versus unemployed workers (Faberman et al., 2022).[21]

Directly Estimated Parameters I assume that workers only face retirement once they enter the oldest age bin (55+) and set the retirement rate to match the average labor force share of workers age 55 in 1990–1994. I set the age-specific search intensity parameters ψ_x to target the age profile of the average job finding rate in 1990–1994. The search intensity of workers in the youngest age bin (25–34) is normalized to 1, and the search intensities for the other bins are set relative to these workers. I set exogenous separation rates δ_y directly to the average job destruction rate by firm age from the BDS in 1990–1994.[22] I set the mass of firms by firm age $\bar{m}(y)$ directly to its empirical value. I calculate this value by taking the ratio of the number of firms in each age bin to the total number of workers in the labor force, HP-filtering the resulting series with an annual smoothing parameter,

[21]See Baley et al. (2022) for a similar implementation of this estimation strategy for worker search intensity.

[22]The Census Bureau defines the job destruction rate as the sum of all employment losses from contracting establishments, including establishments shutting down, divided by total employment. It therefore includes employment losses both from employees leaving the firm (continuing firms) and from firm exits (firm deaths). This is the relevant definition of match separation in my model since the boundaries of the firm within a firm age bin are undefined.

Table 2: Model Calibration

Parameter		Bin	Value	Target	Data	Model
Panel A: Externally Set						
β	Discount factor	–	0.996	5% annual real interest rate		–
α	meeting function elasticity	–	0.8	Lange and Papageorgiou (2020)		–
κ_e	Employed search intensity	–	0.5	Faberman et al. (2022)		–
κ_u	Unemployed search intensity	–	1	Normalization		–
Panel B: Directly Estimated						
ω_x	Retirement rate	55+	0.016	Labor force share 55+	0.147	0.147
ψ_x	Search intensity by worker age bin	25–34	1.000	Job finding rate by worker age bin	0.285	0.276
		35–44	0.901		0.256	0.249
		45–54	0.825		0.235	0.220
		55+	0.684		0.195	0.189
δ_y	Separation rate by firm age bin	0–1	0.033	Job destruction rate by firm age bin	0.033	0.033
		2–3	0.026		0.026	0.026
		4–5	0.020		0.020	0.020
		6–10	0.017		0.017	0.017
		11+	0.012		0.012	0.012
$\bar{m}(y)$	Steady-state mass of firms by firm age bin	0–1	0.014	Number of firms-per-worker by firm age bin	0.014	0.014
		2–3	0.010		0.010	0.010
		4–5	0.008		0.008	0.008
		6–10	0.015		0.015	0.015
		11+	0.030		0.030	0.030
Panel C: Internally Estimated						
c_0	c_y level parameter	–	0.181	Job finding rate	0.256	0.243
c_1	c_y slope parameter	–	0.829	Average firm size by firm age bin	See Figure 3	
c_2	c_y curvature parameter	–	1.155		See Figure 3	
p_0	p_y level parameter	–	2.186	Average earnings by firm age bin	See Figure 3	
p_1	p_y slope parameter	–	0.207		See Figure 3	
p_2	p_y curvature parameter	–	-0.077		See Figure 3	
b_0	b scale parameter	–	0.899		See Figure 3	

Notes: The frequency is monthly. For more details on moment construction, see Appendix A.4.

and extracting the value in 1994. Given average exit rates ζ_y from the BDS in 1990–1994, I then back out the steady state entry rate $\bar{\gamma}$ and entry cost $\bar{\chi}$ that corresponds to $\bar{m}(y)$.

Internally Estimated Parameters To estimate the parameters that govern the vacancy cost level c_y, match output p_y, and unemployment benefit b, I target the aggregate job finding rate, average firm size by firm age, and average earnings by firm age.[23] Though

[23] I use data from the CPS, BDS, and QWI to compute these moments and take averages over the period 1990–1994. In total, I estimate 7 parameters to match 11 bin-level moments in the data, meaning that the model

these parameters are jointly identified by the moments in the data, it is useful to consider which moments in particular inform specific parameters.

First, the parameters in the vacancy cost function pin down average firm size across firms as well as the overall scale of the economy. The equation below shows the solution for the number of vacancies $v_t(y)$ posted by firms in each age bin.[24]

$$v_t(y) = m_t(y)\, \frac{\mu_t \cdot J_t(y)}{c_y}$$

From this equation, we can see how c_y shifts up or down the number of vacancies posted by firms of each age, ceteris paribus. Appropriately setting the parameters (c_0, c_1, c_2) pins down the vacancy distribution and therefore the size of firms in each age bin. Moreover, they control the *total* number of vacancies in the economy, which influences the contact rate λ_t and hence the job finding rate out of unemployment.

Next, output p_y and unemployment benefit b enter directly into the wage equation, which I reproduce below (time subscripts are suppressed to conserve on notation). They also affect the shape of the surplus function $S(x, y)$ and therefore enter wages indirectly through the *Expected Renegotiation Benefit* term, which captures the amount a worker is willing to have deducted from her wages in order to accept a job on a certain rung of the job ladder. It is higher (wages are lower) when she expects many opportunities to renegotiate her wages upward in the future.

$$w(x, y, \sigma) = \sigma p_y + (1-\sigma)b - (1-\omega_x)(1-\delta_y)\beta \underbrace{\mathrm{E}\left[\mathbb{1}\{S(x', y') \geq 0\}\phi_x \lambda \int R(x', y', \sigma, y'') \frac{v(y'')}{V}\, \mathrm{d}\, y''\right]}_{\text{Expected Renegotiation Benefit}}$$

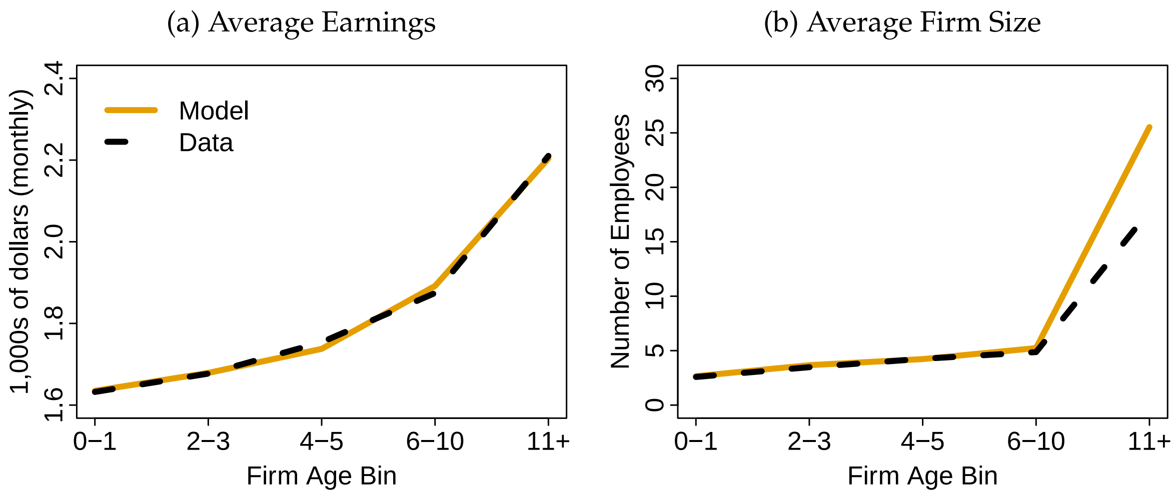
Hence, the parameters (p_0, p_1, p_2) primarily determine the wage profile across firm age, as they control the share of the surplus a worker can command at a particular firm as well as any future surplus she expects to receive. Lastly, the scaling parameter b_0 influences the lowest wages workers are willing to accept when hired out of unemployment.[25]

is overidentified. Appendix A.4 contains additional details on moment construction.

[24] This expression can be derived by combining the definition of $v_t(y)$, the expression for the vacancy posting cost function $C_y(\cdot)$, and Equation 5, and then solving for $v_t(y)$.

[25] In the model, if unemployment becomes "too costly" – i.e. b is very low relative to p_y – then workers accept very low wages (even negative) in order to "buy their way" onto the job ladder. This well-known feature of the sequential auctions bargaining protocol is especially strong when workers have zero bargaining power out of unemployment, as I assume in order to keep the model tractable. However, setting b_0 sufficiently high helps mitigate this effect so that wages remain positive.

Figure 3: Model Fit: Targeted Moments



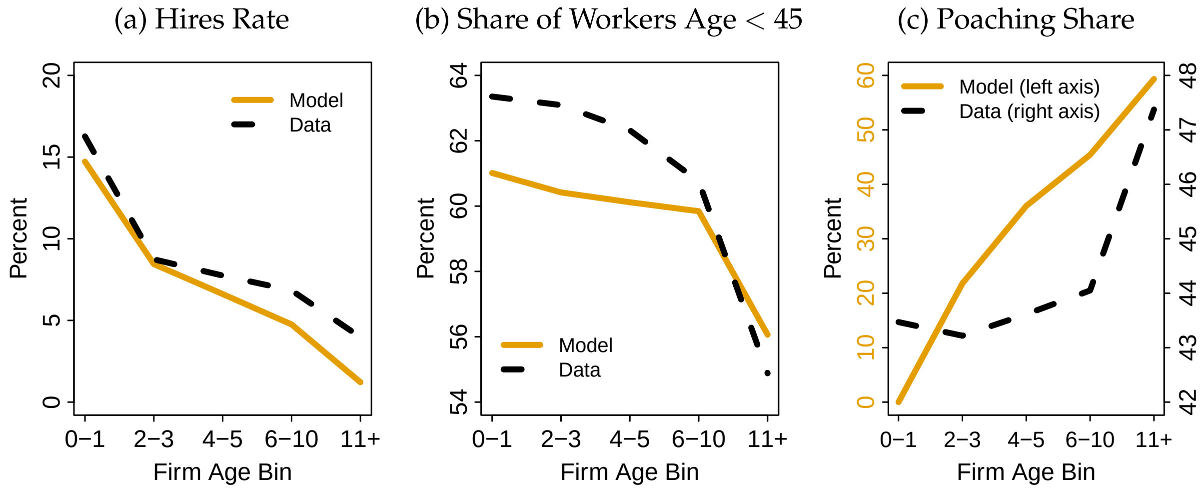
Notes: In each panel, the orange solid lines show the model moments and the black dashed lines show the corresponding data moments. Data on average earnings and average firm size by firm age are from the QWI and BDS, respectively. See Appendix A.4 for details on moment construction.

4.2 Model Fit

The last two columns of Table 2 compare the estimated moments in the model to their counterparts in the data. First, the job finding rate is slightly underestimated at roughly 24% in the model versus 25% in the data. The remaining data moments are taken across the firm age grid, so I display the estimated parameter values in Table 2 and plot the model fit in Figure 3. Overall, the model achieves a reasonably good fit, with an objective function value of about 13 percent. Panel 3a in the figure shows that the model matches the wage profile by firm age. The estimated parameters of the match-level output function p_y imply that productivity is increasing and concave in firm age. Hence, the oldest firms in the economy are the most productive and pay the highest wages. As in the data, average wages paid by firms in the oldest age bin (11+ years old) are about 1.3 times higher than average wages paid by firms in the youngest age bin (0–1 years old) in the model. Panel 3b in the figure shows that the model closely matches average firm size by firm age, with the exception of the oldest firms. The estimated parameters of the vacancy cost level c_y imply that vacancy costs are increasing and convex in firm age. Hence, the oldest firms face the highest per-unit vacancy posting costs. The oldest firms in the model are also the largest, with an average size of about 25 employees (versus 18 in the data).[26]

[26]Dropping the aggregate job finding rate from the vector of targeted moments allows the model to match average firm size by firm age exactly, but results in a job finding rate of about 4%, which is far too low relative to the data. This is because the model needs a sufficient amount of vacancy posting at large, old firms in order to match the magnitude of the job finding rate in the data. Moreover, overstating the size of

Figure 4: Model Fit: Non-Targeted Moments, Firm Age

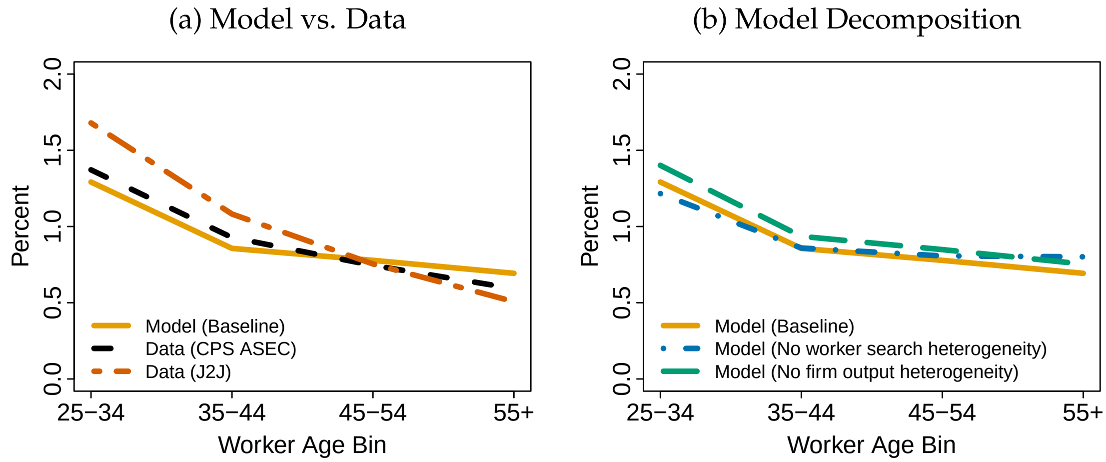


Notes: In each panel, the orange solid lines show the model moments and the black dashed lines show the corresponding data moments. Data are from the Census Bureau's Job-to-Job Flows (J2J) and QWI databases. See Appendix A.4 for details on moment construction.

Non-Targeted Moments Figure 4 shows that the model captures other moments in the data that vary across the firm age distribution. First, younger firms grow faster than older firms and therefore have a higher ratio of hires-to-employment (panel 4a). Next, the model captures the life-cycle sorting patterns I document in Section 2. In the model as in the data, younger firms employ a higher share of younger workers (panel 4b). Last, the model captures the evolution of the poaching share – the fraction of hires that are poached from other firms rather than hired from the unemployment pool – across the firm life cycle (panel 4c). Relative poaching shares in the model determine the direction of net job ladder moves; because old firms sit at the top of the job ladder, they have the highest poaching shares (Bagger and Lentz, 2019). Although the magnitude is overstated relative to the data, the model captures the qualitative implication that poaching shares increase over the firm life cycle, on average. The model generates this pattern through the following channel: young workers join the unemployment pool and search for jobs when they enter the labor market; young firms sit at the bottom of the job ladder and therefore hire exclusively from the unemployment pool; because younger firms have a larger share of hires from unemployment and younger workers are more likely to be unemployed, the

old firms in the model and understating the average vacancy posting costs they face works against finding large effects of a decline in firm entry on labor market outcomes. If old, large firms are both very productive and very responsive to changes in aggregate labor market conditions, they could offset shocks to the labor market by changing their hiring behavior. Therefore, I argue that this small discrepancy in average firm size in the model versus data does not substantially affect my results and if anything could moderate them.

Figure 5: Model Fit: Job-to-Job Flows



Notes: The left panel shows the rate of job-to-job flows in the estimated model compared to the data. Black, dashed lines show data from the CPS ASEC, following the methodology of Molloy et al. (2016). Red, dot-dashed lines show data from the Census Bureau's J2J. The right panel shows the rate of job-to-job flows in the estimated model compared to two counterfactual scenarios. Blue, dash-dot lines show this moment when worker search intensity ψ_x is set to a common value. Green, dashed lines show this moment when firm output p_y is set to a common value.

share of younger workers at younger firms is larger.[27] Therefore, capturing the poaching share across firm age determines the life-cycle sorting patterns of employment.

Figure 5 displays the job-to-job flow rate over the worker life cycle in both the model and the data. Panel 5a shows that job-to-job moves in the model decline as workers age and closely follow the pattern found in two different data series: one derived from the Annual Social and Economic Supplement (ASEC) of the Current Population Survey (CPS) and the other from the Census Bureau's J2J database. In the model, relative worker search intensity and job ladder position – young workers occupy lower rungs of the job ladder, on average, and are therefore more likely to switch jobs if contacted by a firm – both help account for this pattern. However, panel 5b shows that this relationship is preserved even after shutting down worker search intensity (ψ_x) and firm output heterogeneity (p_y). Therefore, the life-cycle profile of job-to-job flows primarily result from workers' relative positions on the job ladder that evolve over their careers.

Discussion Firms differ across the life cycle along several dimensions, and the goal of the estimation strategy is to capture those that are relevant for the job ladder mechanism

[27]In the estimated model, *all* hires for firms in the youngest age group come from unemployment (poaching share = 0). Adding firm heterogeneity within firm age bins could allow the model to quantitatively replicate poaching shares in the data, but as long as the poaching share increases over the firm life cycle on average, the main mechanism is preserved.

at the heart of the model. First, young firms are more likely to shut down than older firms, on average. The model captures this dynamic through the declining profile of exit rates ζ_y and separation rates δ_y by firm age, both of which I infer directly from the data. Next, young and old firms have different productivity levels, on average. The model captures these differences through the output function p_y, which I estimate to be increasing in firm age, reflecting either growth or selection effects (Hopenhayn, 1992). Last, young and old firms may face different costs of expansion, which the model captures through vacancy costs c_y. I estimate that average vacancy posting costs are higher for old firms, indicating that it is easier for younger firms to expand (Haltiwanger et al., 2013).[28]

5 Quantifying the Effects of Declining Business Dynamism

I now simulate a decline in business dynamism in the estimated model and quantify its impact on workers' careers. Starting from the initial steady state firm distribution in 1994, I back out the firm entry rate to match the evolution of the number of firms-per-worker in the data, holding firm exit rates fixed at their initial values. I first describe how I calibrate the change in firm entry below. Then, I discuss the effects of declining dynamism on labor market outcomes in the aggregate and across cohorts of workers.

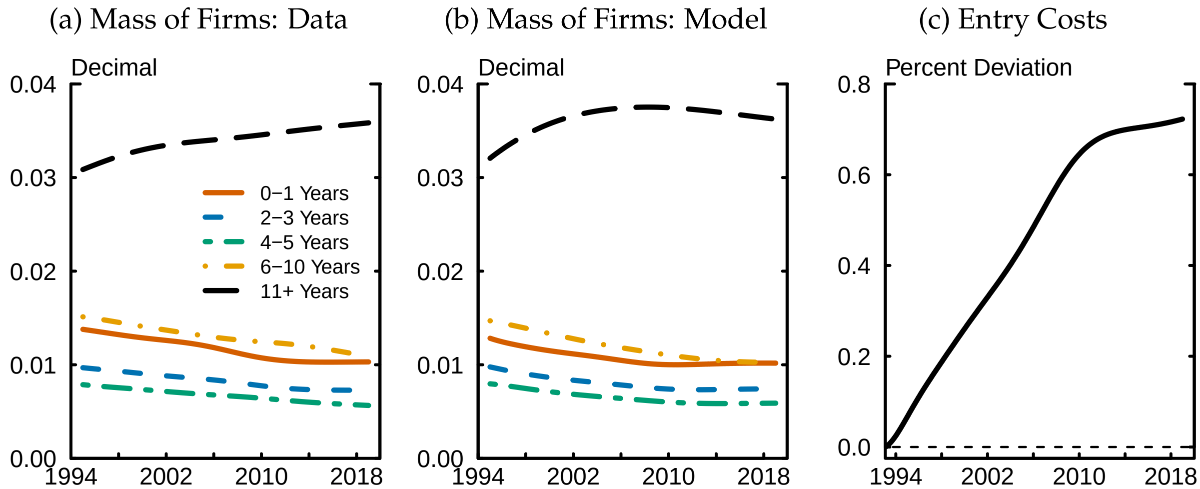
Entry Cost Shock Calibration According to the zero-profit condition in Equation 13, the firm entry rate γ_t adjusts such that expected discounted surplus for new entrants net of the entry cost χ_t is zero. In order to simulate a decline in the firm entry rate, I calibrate a shock to the entry cost χ_t such that the time path of the mass of firms is as close to the data as possible. Holding exit rates by firm age constant, I impute the entry rate γ_t to match the number of firms-per-worker $\mathcal{M}_t$ in the data. Along the transition path, the number of firms-per-worker declines by about 10%. Figure 6 shows the resulting process for the mass of firms by firm age and for entry costs, which increase by about 0.8% in terms of units of output. I feed this process into the model and study the response of the economy.

5.1 Effects on the Labor Market

Figures 7 and 8 show the effects of the increase in entry costs on labor market stocks and flows. As the number of firms-per-worker declines, aggregate vacancies (Equation 6) in the economy decreases. Aggregate vacancies are made up of two components. The first is

[28] Different underlying forces could lead to firm dynamics of this nature. Rather than explicitly microfounding these mechanisms, the estimated model provides a reduced-form accounting of the firm life cycle.

Figure 6: Calibrating the Firm Entry Rate



Notes: The mass of firms by firm age bin is the ratio of the number of firms in the respective age bin to the total number of workers in the labor force. Data are from the BDS and the Bureau of Labor Statistics (BLS) Labor Force Statistics (LFS) database, respectively. Sample includes only male workers age 25 and over. Series are HP-filtered using an annual smoothing parameter. Entry costs are expressed in units of output.

the number of firm-level vacancies $n_t(y)$, which are pinned down by the vacancy creation condition (Equation 5). Firm-level vacancies are then scaled by the total number of firms in each age bin $m_t(y)$. Due to the decline in the entry rate, the total number of firms-per-worker declines, which directly decreases V_t. The magnitude of the decrease in V_t then depends on the degree to which firm-level vacancies $n_t(y) = \frac{\mu_t \cdot J_t(y)}{c_y}$ respond to the drop in dynamism, which is determined by changes in the expected value of a filled vacancy $J_t(y)$ and the rate at which firms contact workers μ_t.

Along the transition path, the expected value of a filled vacancy $J_t(y)$ increases because there are more unemployed workers searching for jobs.[29] In addition, the firm contact rate μ_t does not respond, remaining at a corner solution where a firm posting vacancies will certainly contact a worker. This corner solution arises from the meeting function because the total mass of firms is much smaller than the total mass of workers in the estimated model.[30] Therefore, the number of firm level vacancies $n_t(y)$ increases slightly along the transition path because of an increase in the expected value of posting a vacancy $J_t(y)$. However, this positive, indirect effect on V_t is not enough to offset the negative, direct effect of a decline in the number of firms-per-worker on V_t.

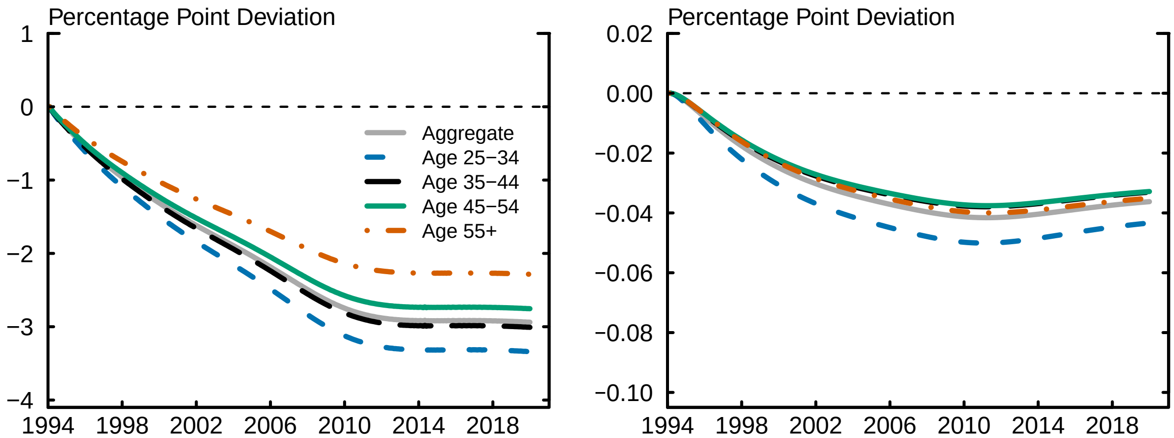
[29] Job creation incentives in the model as captured by $J_t(y)$ are quite sensitive to changes in the stock of unemployed workers, who search with a higher intensity than employed workers (Equation 4)

[30] Total meetings in the economy cannot be lower than the total mass of effective searchers or the total number of aggregate vacancies. Total meetings are equal to $\min\{L_t, V_t, \Psi(L_t, V_t)\}$.

Figure 7: Effects on Labor Market Flows

(a) Job Finding Rate by Age Group

(b) Job Separation Rate by Age Group



Notes: Figure shows model-simulated outcomes along the transition path of the economy.

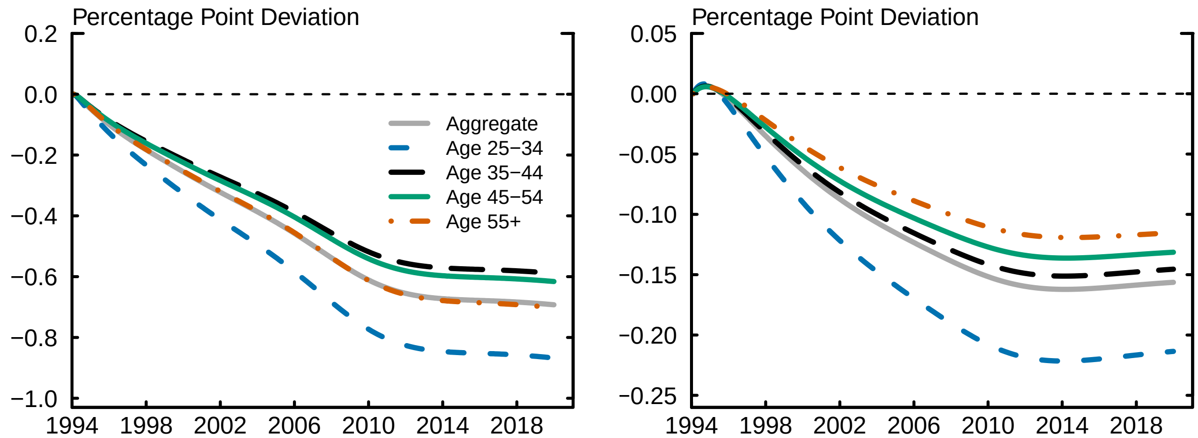
The decline in V_t implies that the contact rate for workers λ_t, which is proportional to V_t, falls along the transition path. Figure 7a shows that the aggregate job finding rate out of unemployment, which is equal to λ_t, declines by about 3 percentage points along the transition path. Younger workers have higher search intensity than older workers, and therefore experience larger drops in their job finding rates. Next, job separation rates (Figure 7b) in the economy fall by about 0.04 percentage points because of a composition effect. As the share of young firms, which have higher job destruction rates, declines, the share of workers matched with older firms, which have lower job destruction rates, increases on the margin. This channel is especially strong for younger workers because they are more highly sorted into young firms in the initial steady state. The combination of a large decline in job finding and a smaller decline in job separation produces a decline in employment rates. Hence, total employment in the economy declines because of lower overall labor demand, with heterogeneous effects across the worker life cycle.

Figure 8 shows that the youngest age group (25–34 years old) experiences the largest decline in employment. Likewise, worker mobility as measured by the job-to-job flow rate also declines, with larger effects for younger worker age groups. The job-to-job flow rate also scales with the contact rate λ_t, but it is additionally influenced by the degree to which workers of different age groups are situated on high versus low rungs of the job ladder. Older workers have had more time to search for suitable matches and are on higher rungs of the job ladder. They therefore switch jobs less often on average and are less exposed to the dynamism induced decline in labor demand. Consequently, the largest effects on worker mobility both in terms of movements out of unemployment and

Figure 8: Effects on Mobility and Employment

(a) Employment Rate by Age Group

(b) Job-to-Job Flow Rate by Age Group



Notes: Figure shows model-simulated outcomes along the transition path of the economy.

in terms of job switching are present for the youngest worker age group.

Contribution to Labor Market Trends I now examine the degree to which these effects explain the evolution of labor market variables in the data between 1994–2019. Table 3 shows the contribution of declining dynamism to changes in labor market outcomes.

Between 1994 and 2019, males age 25 years and older experienced a decline in both mobility and employment rates. In the data, the rate at which workers switch between jobs at different firms fell by about 0.35 percentage points on a monthly basis. Through the lens of the model, the decline in business dynamism accounts for about 45% of this decline. Moreover, the decline in employer switching was not uniform across worker age groups. In particular, employer switching fell by more for younger worker age groups. In the model as in the data, employer switching rates for younger workers decline by more in response to the decline in the firm entry rate. The degree to which the model accounts for this pattern varies across age group, but it is at least 40% for all age groups.[31]

Table 3 also shows that male workers between the ages of 25 and 54 experienced a decline in the employment rate (employment-to-population ratio) over this time horizon. Because the workers in these demographic groups are highly attached to the labor force, I compare trends in employment-to-population ratios in the data to model-implied changes in employment rates. Through the lens of the model, the decline in business dynamism accounts for about 15% of the decline in the aggregate employment-to-population ratio between 1994 and 2019. It accounts for a slightly larger share, between

[31]For the oldest worker age group, the decline in employer switching is larger in the model than in the data.

Table 3: Quantifying the Effects of Declining Dynamism

Change: 1994–to–2019	Model	Data	Explained
Employer Switching Rate			
Aggregate	-0.16 pp	-0.35 pp	45.0%
Age 25-34	-0.21 pp	-0.51 pp	42.3%
Age 35-44	-0.15 pp	-0.25 pp	59.2%
Age 45-54	-0.13 pp	-0.12 pp	112.9%
Employment–to–Population Ratio			
Aggregate	-0.69 pp	-4.37 pp	15.8%
Age 25-34	-0.87 pp	-2.81 pp	30.9%
Age 35-44	-0.59 pp	-1.24 pp	47.6%
Age 45-54	-0.62 pp	-1.97 pp	31.3%

Notes: Model and Data columns show changes between 1994 and 2019 in percentage points (pp). Explained column shows the ratio of the Model column to the Data column, as a percentage. The employer switching rate is defined as the percentage of employed workers who switched employers at least once in a year and is constructed using the CPS ASEC following the methodology of Molloy et al. (2016). Employment–to–population ratio is from the BLS LFS database. Sample includes only male workers age 25 and older. Series are HP-filtered using an annual smoothing parameter.

30 and 50 percent, of the empirical trends in employment rates across worker age groups. Overall, the model can account for a significant share of important labor market trends over the last few decades.

5.2 Accounting for Demographic Change

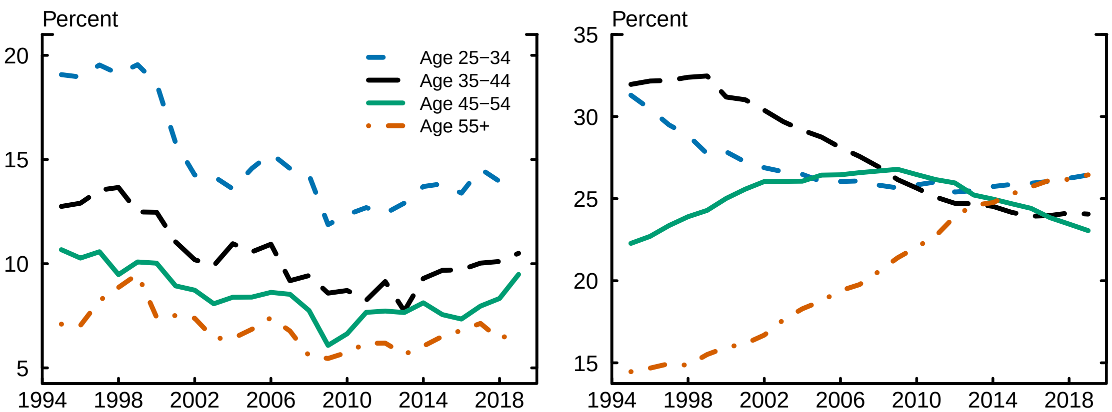
Demographic change and the resulting slowdown of labor force growth has emerged as a primary explanation for the decline in the firm entry rate in the U.S. (Hopenhayn et al., 2022; Karahan et al., 2024). Although the decline in employer switching (Figure 9a) was larger for younger workers, the share of younger workers (Figure 9b) also declined considerably over this time horizon. Therefore, the changing age composition of the labor force could have mechanically reduced the aggregate employer switching rate. In this section, I show that this is not the case and that the business dynamism induced decline in employer switching is consistent with the patterns in the data.

To assess whether the changing age composition of the U.S. labor force is responsible for the *aggregate* decline in job switching, I perform the following shift-share analysis. Let $EE_{a,t}$ denote the job switching rate and $\pi_{a,t}$ denote the labor force share of worker age group a.[32] I decompose changes in the aggregate job switching rate EE_t by hold-

[32] I use the same age bins as in the model and data analysis sections. Results are robust to using employment

Figure 9: Employer Switching and Demographic Change

(a) Employer Switching by Age Group (b) Labor Force Share by Age Group



Notes: The employer switching rate is defined as the percentage of employed workers who switched employers at least once in a year and is constructed using the ASEC supplement of the CPS, following the methodology of Molloy et al. (2016). Labor force share is from the LFS database. Sample includes only male workers.

ing either $EE_{a,t}$ or $\pi_{a,t}$ fixed at 1994 values and allowing the other to vary. The *Within* component captures the influence of age group specific changes in job switching on the aggregate rate, holding labor force shares constant, and the *Between* component captures the influence of demographic change, holding the life-cycle profile of the job switching rate constant; the *Interaction* term captures the residual where both are allowed to vary.

$$\Delta EE_t = \underbrace{\sum_a \Delta EE_{a,t} \times \pi_{a,0}}_{Within} + \underbrace{\sum_a EE_{a,0} \times \Delta\pi_{a,t}}_{Between} + \underbrace{\sum_a \Delta EE_{a,t} \times \Delta\pi_{a,t}}_{Interaction}$$

Table 4 shows the results of this decomposition for 1994–2019. I find that the within component accounts for the majority of the decline in aggregate employer switching over this time horizon; it is responsible for over 80% of the decline. Hence, the larger declines in EE mobility among younger worker cohorts actually drive the bulk of the *aggregate* change in EE mobility. I now perform the same decomposition in the model and compare the results to the data in order to assess the effects of demographic change on my results.

Simulating Demographic Change My baseline results show that through the lens of the model, employer switching declines by more for younger workers in response to the decline in the firm entry rate. However, this does not account for demographic change, as I hold the labor force composition constant. Therefore, I conduct an additional experiment

shares instead of labor force shares.

Table 4: Shift-Share Decomposition of Employer Switching: 1994–2019

	Data				Model			
	Total	*Within*	*Between*	*Interaction*	*Total*	*Within*	*Between*	*Interaction*
Change (pp)	-0.33	-0.27	-0.10	0.04	-0.31	-0.29	-0.12	0.10
Explained (%)	100.0	82.2	29.4	-11.6	100.0	93.3	39.8	-33.1

Notes: Data on employer switching rates and labor force shares are from the CPS and LFS, respectively. Sample includes only male workers. Rates converted to monthly in the data to align with the model.

whereby I allow the labor force composition to vary as in the data. In particular, I hold retirement rates ω_x constant and back out the labor force entry rate η_t so as to match the change in the labor force share of age 55+ workers over 1994–2019 (Figure 9b). I then feed the calibrated laws of motion for *both* the worker distribution $\ell_t(x)$ and the firm distribution $m_t(y)$ into the model and study the results along the transition path.[33]

Table 4 also shows the results of performing the same shift-share decomposition in the model. Remarkably, the within component accounts for the majority of the decline in the aggregate employer switching rate, as in the data. The aggregate decline in job ladder mobility results primarily from age-group-specific trends stemming from the decline in young firms in the economy. Therefore, I argue that the decline in firm entry and the associated shift of the firm age distribution was a driving force of the change in job ladder mobility across the worker life cycle.

5.3 Welfare Implications

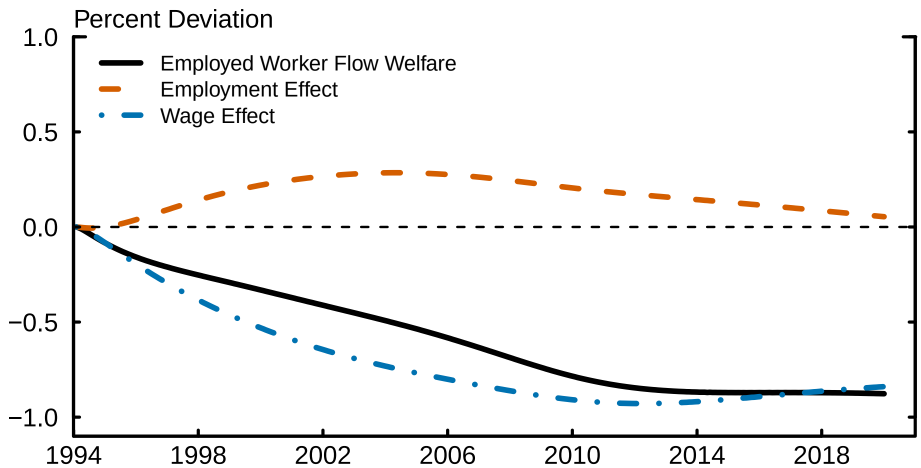
Lastly, I examine the consequences of the decline in business dynamism for worker welfare in the aggregate and at different stages of the life cycle. I return to the experiment where I hold worker labor force shares constant and allow the firm law of motion to evolve as in the data. I first describe the welfare measures I use in my analysis and then decompose welfare in the economy along several dimensions. This analysis also serves to shed light on the key mechanisms at play along the transition path.

Welfare Measure The flow welfare value of employed workers is defined as:

$$\tilde{w}_t \equiv \int \int w_t(x, y) e_t(x, y) \, \mathrm{d}\, x \, \mathrm{d}\, y$$

[33] I re-normalize $\mathcal{M}_t$ such that the number of firms-per-worker matches the data.

Figure 10: Employed Worker Flow Welfare Decomposition



Notes: Figure shows model-simulated outcomes along the transition path.

where $e_t(x, y)$ is total employment among age x workers and age y firms and $w_t(x, y)$ is the wage rate paid by age y firms to age x workers.[34]

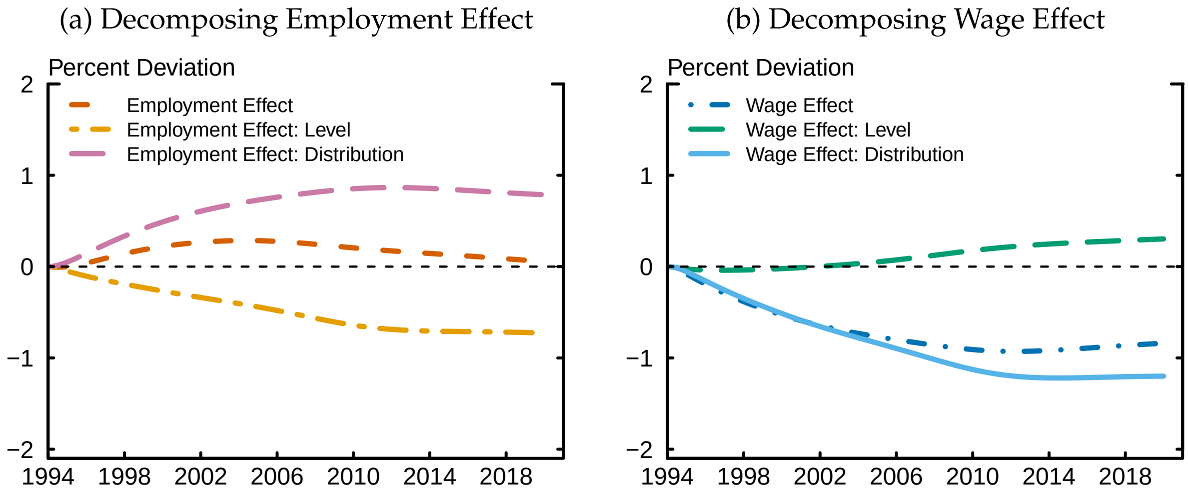
Welfare Decomposition I now decompose changes in employed workers' welfare $\tilde{w}_t$ into two margins. The first margin stems from changes in employment rates, while the second margin stems from changes in workers' wages. Let $e_0(x, y)$ denote match-level employment in steady state and let $w_0(x, y)$ denote match-level wages in steady state for matches between workers of age x and firms of age y. The percentage deviation of employed workers' welfare from steady state can be approximated (to first order) as:

$$\Delta \tilde{w}_t \approx \underbrace{\Delta \left(\int \int e_t(x, y) w_0(x, y) \, \mathrm{d}\, x \, \mathrm{d}\, y \right)}_{\textit{Employment Effect}} + \underbrace{\Delta \left(\int \int e_0(x, y) w_t(x, y) \, \mathrm{d}\, x \, \mathrm{d}\, y \right)}_{\textit{Wage Effect}} \tag{14}$$

Intuitively, employed worker flow welfare may change due to changes in the number of workers that are employed or to changes in the wages workers earn while employed. In the above expression, the *Employment Effect* term captures the degree to which $\tilde{w}_t$ changes due to changes in employment in the economy, holding match-level wages constant at their steady state value. The *Wage Effect* term captures the degree to which employed worker welfare $\tilde{w}_t$ changes due to changes in match-level wages, holding employment by worker and firm age constant at its steady state value.

[34]The most natural measure of welfare in the model would be the value function for unemployed workers $B_t(x)$. However, this is exogenously pinned down by the wage bargaining protocol, so I instead use a flow value concept of welfare.

Figure 11: Level Effect and Distribution Effect



Notes: Figure shows model-simulated outcomes along the transition path of the economy.

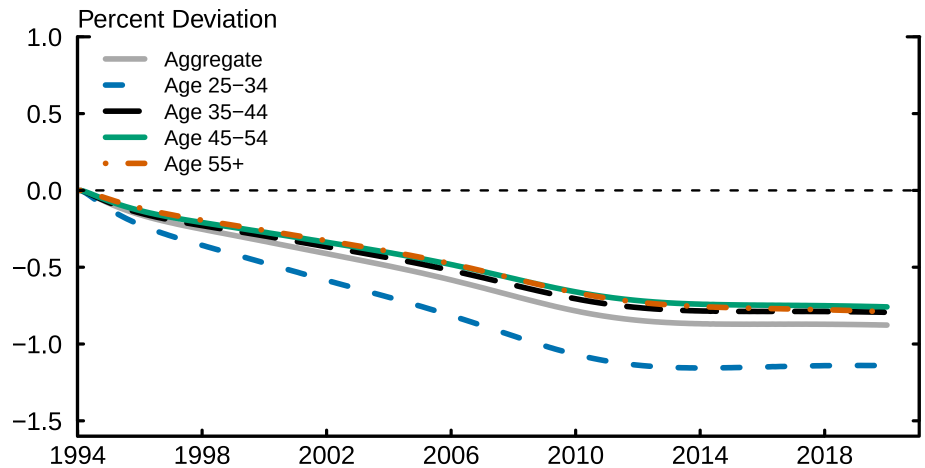
Figure 10 plots this decomposition. It is clear from the figure that the *Wage Effect* dominates, driving the overall decline in employed worker flow welfare. Along the transition path, employed workers receive lower wages, driven by lower between-firm poaching competition as captured by λ_t. Although the employment probability declines in response to the decline in business dynamism, the *Employment Effect* plays only a small role in the decline in employed workers flow welfare because workers also sort into matches that pay higher wages, on average. To further inspect the underlying sorting patterns that drive the *Employment Effect* and the *Wage Effect*, I now further decompose them into components stemming from changes in their levels versus distributions.[35]

Figure 11 plots this decomposition. First, we can see that the *Employment Effect* is driven by offsetting changes in the level and distribution (left panel). While overall employment falls along the transition path (level effect), workers on average sort into better matches (distribution effect), such that the match distribution shifts toward matches that pay higher wages. The former effect is present because as firm entry declines, there are fewer firms in the economy, providing fewer employment opportunities for workers. The latter effect is present because as firm entry declines, the firm age distribution shifts toward older firms that are more productive and pay higher wages.

Similar dynamics shape the evolution of the *Wage Effect* (right panel). On average, workers with a given level of the surplus share σ_t experience only small changes in their wages paid (level effect). Workers higher up on the within-match job ladder with higher surplus share all else equal have a slight decline in wages, but this is offset by a decline

[35] Appendix D.5 provides formulas for these decompositions.

Figure 12: Worker Flow Welfare by Age Group



in wages among workers lower down on the within-match job ladder. In other words, the wage-bargaining share profile flattens within matches, on average. However, workers face a lower probability of moving up the job ladder due to the decline in business dynamism and are on average stuck in lower rungs of the job ladder (distribution effect). In other words, the match distribution shifts toward matches with lower surplus share. The net effect is that wages fall along the transition path, as workers command a lower share of the match surplus in the economy, on average.

Welfare Across Cohorts Lastly, I explore the welfare implications of declining business dynamism across worker age groups. As is clear from the section above, younger age groups experience larger declines in both mobility and employment rates in response to the shift in the firm age distribution. Therefore, a decline in business dynamism results in different changes in welfare for workers at different stages of the life cycle.

Figure 12 quantifies the degree to which different worker cohorts experience different declines in flow welfare in response to a decline in business dynamism. While all age groups experience a decline in welfare, younger age groups are hit harder. Aggregate worker flow welfare falls by about 0.9 percent along the transition path, while the youngest age group of workers (25–34) experiences more than a 1 percent decline in welfare. The larger decline in flow welfare for younger workers is driven by their larger declines in both the *Employment Effect* and the *Wage Effect*. Along the transition path, employment levels decline by more for younger workers. Moreover, younger workers stand to benefit less from the increasing share of older, more productive firms because they sort into matches at these firms at a lower rate. Additionally, because younger workers experience larger declines in mobility rates, the decline in the distribution component of the

Wage Effect is larger for these groups, as they are unable to move out of the lower rungs on the job ladder. These effects combine to generate a larger decline in flow welfare for younger cohorts.

6 Conclusion

In this paper, I assess the consequences of the recent decline in business dynamism in the United States for labor market outcomes and total welfare in the economy across different cohorts of workers. I first review several empirical patterns that suggest a link between the rate of business dynamism – the share of young relative to old firms in the economy – and labor market mobility along a worker's life cycle. I show that in the data, there has been a decline in the rate at which new firms enter the economy, resulting in a shift of the firm age distribution toward older firms that tend to also be larger. Moreover, I show that young firms are more likely to employ younger workers in that the employment distribution of young firms is on average skewed toward young workers. This suggests that the decline in business dynamism may have disproportionately affected the labor market outcomes of more recent cohorts of workers.

Then, I set up a model of labor market sorting between heterogeneous firms and heterogeneous workers subject to search frictions in order to assess this hypothesis. In the model, workers differ by the length of time since they entered the labor market and firms differ by the length of time since they entered the economy. I calibrate the model to match several features of the labor market in 1994 and then simulate a decline in business dynamism in line with the data. I find that aggregate employment declines along the transition path, leading to a decline in total welfare in the economy. However, these effects are not felt equally by all workers. Younger workers are more exposed to changes in business dynamism, as they have a larger share of employment at younger firms. Mobility and employment rates decline by more for younger cohorts, leading to a decline in welfare that is more severe for these groups of workers.

A Data Description

A.1 Census Bureau Public Use Data

The Census Bureau publishes tabulations of statistics from the Longitudinal Employer Household Dynamics (LEHD) database – a linked employer-employee dataset constructed from state administrative records – at different levels of aggregation such as industry, geography, firm size and age, as well as worker demographics. It also publishes tabulations of the Longitudinal Business Database (LBD) – a census of business establishments and firms in the U.S. with paid employees comprised of survey and administrative records – at similar levels of aggregation. Though I cannot access the underlying microdata, my analysis uses these publicly available data products (U.S. Census Bureau, 2025a,b).

Quarterly Workforce Indicators (QWI) The Quarterly Workforce Indicators (QWI) are derived from the LEHD and contain information on hires, separations, turnover, employment growth, and earnings by industry, worker demographics, firm age and firm size. The data are available at: `https://lehd.ces.census.gov/data/#qwi`.

Job-to-Job Flows (J2J) The Job-to-Job Flows (J2J) database is derived from the LEHD and contains additional detail on worker flows, such as measures of *direct* job-to-job transitions. The data are available at: `https://lehd.ces.census.gov/data/#j2j`.

Business Dynamics Statistics (BDS) The Business Dynamics Statistics (BDS) datasets contain annual measures of business dynamics such as job creation, job destruction, establishment births and deaths, and firm startups and exits. The data are available for the overall economy as well as by different establishment and firm characteristics. The BDS is derived from the LBD. Data may be downloaded from `https://www.census.gov/data/datasets/time-series/econ/bds/bds-datasets.html`.

A.2 Current Population Survey (CPS)

Annual Social and Economic Supplement (ASEC) To construct the measure of employer switching, I use data from the Annual Social and Economic Supplement (ASEC) of the Current Population Survey (CPS). The ASEC is based on a survey of more than 75,000 U.S. households and contains detailed questions on the social and economic characteristics of each person who is a household member as of the interview date. Questions in the survey pertain to the previous calendar year.

To construct the measure of employer switching used in the paper, I use a variable in ASEC that records the responses to the following survey question: "For how many employers did (name/you) work in [year]? If more than one at the same time, only count it as one employer." Since the question asks respondents to count simultaneous employment at multiple firms as only one employer, any respondent who answers that she had more than one employer in a given year must have switched jobs between firms at some point during that year. The employer switching rate is then estimated as the number of respondents who had more than one employer divided by total employment.[36]

This approach follows Molloy et al. (2016), which is the first paper to my knowledge to construct this specific measure of employer switching. I download the variable `NUMEMPS`, which contains responses to the survey question above, from the IPUMS CPS website (Flood et al., 2024). I select wage and salary workers in the private sector who reported that they were employed or had a job during the previous calendar year. IPUMS CPS data are available at https://cps.ipums.org/cps/.

Longitudinally Linked CPS In order to construct measures of job finding and separation by worker age group, I follow the procedure described in Shimer (2012) to link respondents in the CPS Basic Monthly Survey (BMS) across months. I gather data from IPUMS CPS and link survey respondents across consecutive months using the unique identifier `CPSIDV` (Flood et al., 2024).[37] This variable includes linking criteria that ensures individuals match on age, sex, and race characteristics. After linking individuals, information on their employment status in each month allows me to construct flow probabilities. Specifically, I use the variable `EMPSTAT` to determine whether a given individual was employed (E), unemployed (U), or not-in-the-labor-force (N) in a particular month. I then compute weighted sums of the number of individuals who transition across labor market states using longitudinal weights provided by IPUMS CPS.

The monthly job finding probability $P(UE)_t$ is defined as the fraction of unemployed individuals in month $t-1$ who are employed in month t. The monthly job separation probability $P(EU)_t$ is defined as the fraction of employed individuals in month $t-1$ who are unemployed in month t. Formulas are given below.

$$P(UE)_t = \frac{\#(\text{Unemployed in month } t-1 \text{ who are Employed in month } t)}{\#(\text{Unemployed in month } t-1)}$$

[36] In practice, I weight each observation using the weighting variable ASECWT provided by IPUMS CPS.

[37] See the following link for more information on linking individuals across surveys in the IPUMS CPS data: https://cps.ipums.org/cps/cps_linking_documentation.shtml.

$$P(EU)_t = \frac{\#(\text{Employed in month } t-1 \text{ who are Unemployed in month } t)}{\#(\text{Employed in month } t-1)}$$

The job finding and job separation rates by age group are simply constructed by applying the above formulas for the relevant age sub-sample.

A.3 Labor Force Statistics (LFS)

To construct the employment-to-population ratio and the labor force share of workers in each age group, I use data from the U.S. Bureau of Labor Statistics (BLS) Labor Force Statistics (LFS) database (U.S. Bureau of Labor Statistics, 2025). The LFS contains statistics on U.S. labor force characteristics tabulated by different demographic groups such as age, race, sex, education, and marital status. I obtain the series listed in Table A.1 from the BLS website. The fraction of age 55 or older workers is simply the number of age 55 or older workers in the civilian labor force divided by the number of age 25 or older workers in the civilian labor force. The data are available at `https://www.bls.gov/cps/`.

Table A.1: Variables in the LFS

Series ID	Labor Force Status	Demographic Group
`LNS11000164`	Civilian labor force	Men, age 25 to 34 years
`LNS12300164`	Employment-population ratio	Men, age 25 to 34 years
`LNS11000173`	Civilian labor force	Men, age 35 to 44 years
`LNS12300173`	Employment-population ratio	Men, age 35 to 44 years
`LNS11000182`	Civilian labor force	Men, age 45 to 54 years
`LNS12300182`	Employment-population ratio	Men, age 45 to 54 years
`LNS11024231`	Civilian labor force	Men, age 55 years and older
`LNS12324231`	Employment-population ratio	Men, age 55 years and older

Notes: Series are at the monthly frequency and are seasonally adjusted by the BLS.

A.4 Constructing Data Moments

Table A.2 summarizes the data moments and their sources. Below, I provide additional detail about how I construct each moment in the data.

Labor force share To construct the labor force share by worker age group, I download the series in Table A.1 from the LFS at a seasonally adjusted, monthly frequency. The sample includes male workers in the age groups 25–34, 35–44, 45–54, and 55 and older. The size of the aggregate labor force is the sum across these groups. The labor force shares equal the size of the labor force in each group relative to the total.

Table A.2: Data Moments

Moment	Bins	Source
Labor force share	Male workers age {25–34, 35–44, 45–54, 55+}	LFS
Job finding rate	Male workers age {25–34, 35–44, 45–54, 55+}	CPS
Job destruction rate	Firms age {0–1, 2–3, 4–5, 6–10, 11+}	BDS
Firms-per-worker	Firms age {0–1, 2–3, 4–5, 6–10, 11+}	BDS, LFS
Average firm size	Firms age {0–1, 2–3, 4–5, 6–10, 11+}	BDS
Average earnings	Male workers age {25–34, 35–44, 45–54, 55+} & Firms age {0–1, 2–3, 4–5, 6–10, 11+}	QWI
Employment share	Firms age {0–1, 2–3, 4–5, 6–10, 11+}	BDS
Poaching share	Firms age {0–1, 2–3, 4–5, 6–10, 11+}	J2J
Share workers < 45	Firms age {0–1, 2–3, 4–5, 6–10, 11+}	QWI
EU separation rate	Male workers age {25–34, 35–44, 45–54, 55+}	CPS
Job-to-job flow rate	Male workers age {25–34, 35–44, 45–54, 55+}	J2J

Notes: CPS data are from IPUMS CPS. LFS data are from the BLS website. I use the 2021 release of the BDS. I use the R2023Q4 releases of the QWI and J2J.

Job finding rate I construct job finding rates in the CPS as described above. The sample includes only male workers age 25 and older. I take averages within age bins over 1990–1994 in order to set the search intensity by worker age bin parameters ψ_x. I target the average aggregate job finding rate over 1990–1994 in the moment matching exercise.

Job destruction rate Following the BDS, I define the job destruction rate (JDR) as:

$$JDR_{i,t} = \frac{\sum_{i \in s, g_{i,t} < 0} (E_{i,t} - E_{i,t-1})}{0.5 * (E_{i,t} + E_{i,t-1})}$$

for establishments i in group s, where $g_{i,t} = (E_{i,t} - E_{i,t-1})/(0.5 * (E_{i,t} + E_{i,t-1}))$.[38] Job destruction is the sum of all employment losses between year t–1 and t from contracting establishments, including establishments shutting down. I download data by firm age bin from the BDS website and take averages over 1990–1994.

Firms-per-worker The number of firms by firm age bin is from the BDS. The size of the aggregate labor force is constructed as above from the LFS using only male workers age

[38] See https://www.census.gov/programs-surveys/bds/documentation/methodology.html

25 and over. I take the ratio of the number of firms to the size of the aggregate labor force by firm age bin. I then HP-filter each series using an annual smoothing parameter ($\lambda = 100$). The steady state mass of firms by firm age bin $\bar{m}(y)$ is the value in 1994.

Average firm size Data on total employment (`emp`) and total number of firms (`firms`) by firm age bin are from the BDS. Average firm size is the ratio of `emp` to `firms`.

Average earnings There is no intensive margin of labor supply in the model, so the concept of wages is akin to earnings. To estimate the wage profile in the model, I target the profile of average earnings-per-employee by firm age group in the QWI. I use the variable `earns`, which corresponds to average monthly earnings of workers employed for the entire quarter.[39] I construct the average of this series within bins using appropriate employment weights. I average across quarters to obtain a yearly series for each bin.

I then deflate each resulting yearly series by the Consumer Price Index for All Urban Consumers: All Items in U.S. City Average (FRED code: CPIAUCSL). This price index measure uses the years 1982–1984 as the base years. I normalize the units to thousands of dollars so that the units of my resulting average earnings measures are: thousands of 1982–1984 dollars earned per month per worker. I take averages over 1990–1994.

Employment share Data on total employment (`emp`) are from the BDS. Employment share is the ratio of `emp` within a firm age bin to total `emp`.

Poaching share The poaching share is the ratio of job-to-job hires to total hires. I use the J2J variables `j2jhire` and `mhire` to count job-to-job hires and total hires, respectively.[40]

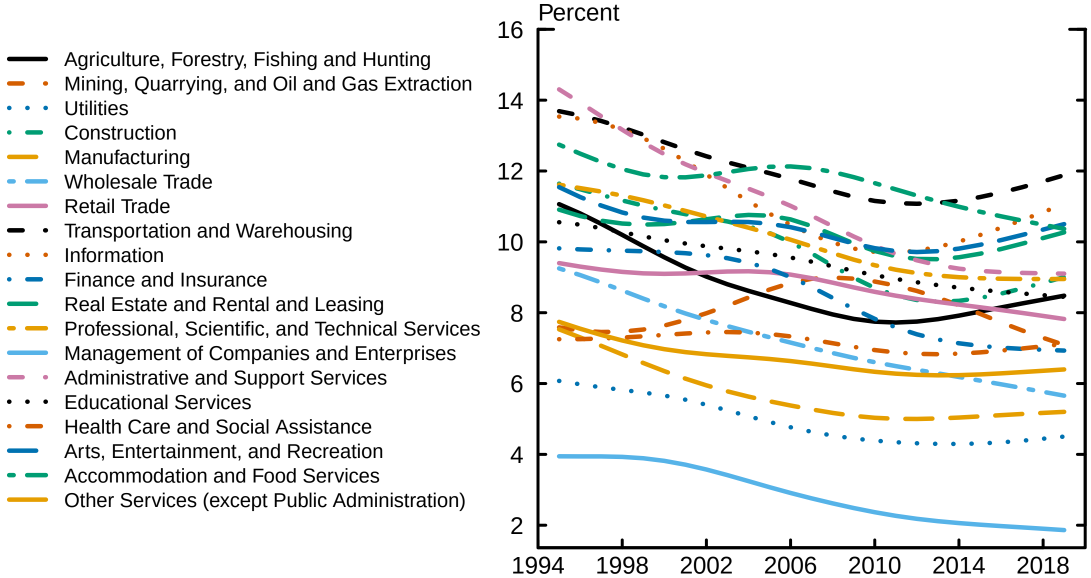
Share workers $<$ 45 I use the QWI to construct the age distribution of employment within each firm age bin. I download QWI estimates tabulated by worker sex/age and firm age at the national level (dataset: `qwi_us_sa_f_gn_ns_op_u.csv`). I select only male workers in the age bins 25–34, 35–44, 45–54, and 55+. The share of workers by age bin within firm age bins is the ratio of total employment by worker age bin, conditional on firm age bin, to total employment within firm age bin. I use the QWI variable `emps` to get a stable measure of employment. I take averages over 1990–1994.

$$\text{Share workers}_{a,f} = \frac{E_{a,f}}{E_f} \quad \text{for worker age bin } a \text{ and firm age bin } f$$

[39]See the following link for variable definitions: `https://lehd.ces.census.gov/doc/QWI_101.pdf`.
[40]See the following link for variable definitions: `https://lehd.ces.census.gov/doc/j2j_101.pdf`

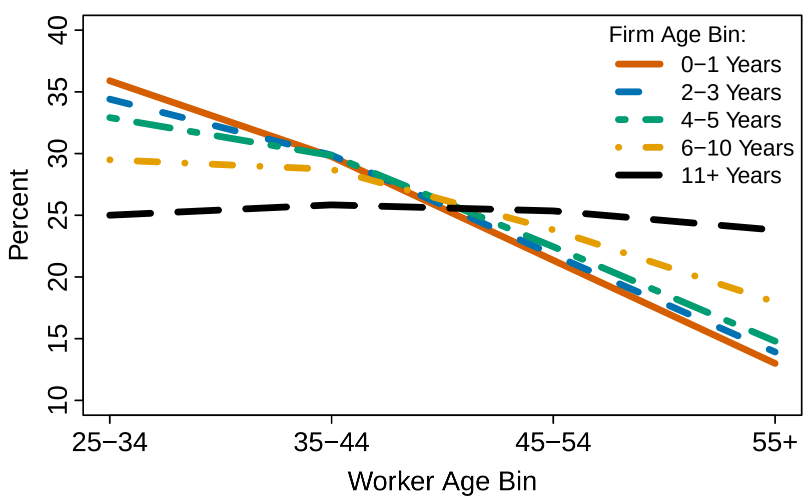
B Additional Figures

Figure B.1: Trends in Firm Entry Rate by Sector



Notes: Entry rate defined as the number of age 0 firms divided by the total number of firms. Data are from the BDS. Series are HP-filtered with an annual smoothing parameter.

Figure B.2: Employment Distribution Across Worker Age by Firm Age, Granular Data



Notes: Figure shows average employment composition, in percentages, across worker age group for firms in different age groups. Data on employment by worker and firm age group are from the QWI. For all series, I include only male workers and take averages over MSA × sector × year cells.

C Robustness

In this section, I conduct robustness checks of the patterns documented in Section 2 in the main text. Table 1 shows that young firms (age 0–10 years) have an employment share of young workers (age 25–44 years) about 15 percentage points higher relative than that of mature firms (age 11 years and older). However, these sorting patterns may be driven by worker and firm characteristics other than age.

For instance, sorting between young workers and young firms may be driven by skill and productivity differences across these groups. A large literature on labor market sorting shows that workers with higher skill levels tend to match with firms with higher productivity levels (Lise and Robin, 2017). To the extent that older workers have been able to achieve higher education levels, and education proxies for worker skill, we may expect to see a higher share of older workers at older firms. Table C.1 explores this possibility.

Table C.1: Worker and Firm Sorting Patterns by Firm Age, Worker Education Groups

	(1)	(2)	(3)	(4)
Firm Age 0–10 Years	-0.235^{***}	-0.390^{***}	-0.328^{***}	0.792^{***}
	(0.029)	(0.030)	(0.038)	(0.091)
Frac. Age 25–44		0.022^{***}	0.020^{***}	0.019^{***}
		(0.001)	(0.001)	(0.001)
ln(Avg. Firm Size)			0.102^{***}	0.234^{***}
			(0.024)	(0.026)
Firm Age 0–10 Years × ln(Avg. Firm Size)				-0.508^{***}
				(0.038)
Year Fixed Effects	X	X	X	X
MSA Fixed Effects	X	X	X	X
Sector Fixed Effects	X	X	X	X
Observations	680,189	675,610	635,595	635,595
R^2	0.618	0.631	0.650	0.650

Notes: Sample includes only male workers age 25 and over for the years 1994–2019. Frac. Age 25–44 is the fraction of a firm's workforce between the ages of 25 and 44. ln(Avg. Firm Size) is the natural logarithm of average firm size. Sector fixed effects are at the 2-digit NAICS level. Standard errors in parentheses. $^{*}p \leq 0.10$;$^{**}p \leq 0.05$;$^{***}p \leq 0.01$.

The table shows the results of regressions similar to those in main text, where instead the outcome variable is the fraction of a firm's work force with a high school education or less. From the first three columns of the table, we can see that younger firms employ a slightly lower fraction of lower skilled workers, though the magnitude of this association is very small and changes sign after controlling for differences in average firm size across firm age groups. Controlling for differences in firm size reveals that larger firms have

Table C.2: Worker and Firm Sorting Patterns by Firm Size, Worker Age Groups

	(1)	(2)	(3)	(4)
Firm Size < 500 Employees	-4.303^{***}	-4.308^{***}	-4.228^{***}	-4.342^{***}
	(0.039)	(0.038)	(0.036)	(0.035)
Frac. Educ. $\leq$ High School				0.058^{***}
				(0.002)
Year Fixed Effects	X	X	X	X
MSA Fixed Effects		X	X	X
Sector Fixed Effects			X	X
Observations	641,174	641,174	641,174	637,340
R^2	0.119	0.157	0.273	0.287

Notes: Sample includes only male workers age 25 and over for the years 1994–2019. Frac. Educ. $\leq$ High School is the fraction of a firm's workforce with less than or equal to a high school education. sector fixed effects are at the 2-digit NAICS level. Standard errors in parentheses. $^{*}p \leq 0.10;^{**} p \leq 0.05;^{***} p \leq 0.01$.

a slightly higher fraction of low skilled workers (Column (3)), but that this pattern is weaker among younger firms (Column (4)). Overall, the results are consistent with some degree of positive assortative matching between high skill workers and high productivity firms, but the firm life cycle also plays a role; some small, yet highly productive young firms likely employ high skill workers in larger proportions. Lastly, the magnitudes of these sorting patterns are much smaller than those documented in Table 1.

To further explore the firm size dimension of worker and firm sorting patterns, I use an indicator for firm size instead of firm age as the independent variable of interest. Table C.2 displays the results. The table shows that smaller firms, on average, have a lower fraction of younger workers relative to firms with 500 employees or more. This pattern remains after controlling for differences in the employment share of low skill workers (Column (4)). Therefore, sorting on worker age and firm age is likely not the result of sorting on and firm size.

Lastly, Table C.3 explores worker skill and firm size sorting patterns directly. The outcome variable in this table is the fraction of workers with less than or equal to a high school education and the independent variable is an indicator for firm size instead of firm age. Here, we can see mostly clearly that even after controlling for differences in age composition across firm size categories, small firms employ a moderately higher fraction of lower skill workers. Again, these patterns are much less stable across different controls and of a much smaller magnitude than those displayed in Table 1. Therefore, I conclude that the sorting patterns between young firms and young workers are not simply masking

Table C.3: Worker and Firm Sorting Patterns by Firm Size, Worker Education Groups

	(1)	(2)	(3)	(4)
Firm Size < 500 Employees	3.841***	3.652***	2.512***	2.623***
	(0.044)	(0.043)	(0.028)	(0.027)
Frac. Age 25–44				0.034***
				(0.001)
Year Fixed Effects	X	X	X	X
MSA Fixed Effects		X	X	X
Sector Fixed Effects			X	X
Observations	641,437	641,437	641,437	637,340
R^2	0.013	0.074	0.630	0.646

Notes: Sample includes only male workers age 25 and over for the years 1994–2019. Frac. Age 25-44 is the fraction of a firm's workforce between the ages of 25 and 44. sector fixed effects are at the 2-digit NAICS level. Standard errors in parentheses. $^{*}p \leq 0.10$;** $p \leq 0.05$;*** $p \leq 0.01$.

differences in worker skill and firm productivity. Instead, the life-cycle component of employment sorting is accounted for by other forces, such as the joint dynamics of young workers and firms, or job ladder position over the life-cycle.

D Derivations and Proofs

Without loss of generality, I normalize search intensity to 1 and abstract from retirement in the derivations below ($\phi_x^i = 1$ and $\omega_x = 0 \, \forall x$). I also suppress the terms in the expectations operator $\mathrm{E}[\cdot]$ to conserve on notation. For unemployed workers, expectations are over values of x' and for any joint value objects, expectations are over combinations of (x', y').

D.1 Unemployed Worker Value Function

The assumption that workers hired out of unemployment have zero bargaining power reduces the unemployed worker's value function to: $B_t(x) = b + \beta \, \mathrm{E}\left[B_{t+1}(x')\right]$.

Proof. Start with the equation for the worker's value of unemployment.

$$B_t(x) = b + \beta \, \mathrm{E}\left[(1 - \lambda_{t+1})B_{t+1}(x') + \lambda_{t+1} \int \max\{W_{t+1}(x', y', y''), B_{t+1}(x')\} \frac{v_{t+1}(y')}{V_{t+1}} dy'\right]$$

Workers hired out of unemployment have zero bargaining power and therefore receive zero surplus share. This implies that $W_t(x,y,y') \equiv W_t(x,y,0) = B_t(x)$.[41] Substituting this into the equation above and reducing the expression yields the desired result.

$$\begin{aligned}
B_t(x) &= b + \beta\,\mathrm{E}\left[(1-\lambda_{t+1})B_{t+1}(x') + \lambda_{t+1}\int \max\{W_{t+1}(x',y',0), B_{t+1}(x')\}\frac{v_{t+1}(y')}{V_{t+1}}dy'\right] \\
&= b + \beta\,\mathrm{E}\left[(1-\lambda_{t+1})B_{t+1}(x') + \lambda_{t+1}\int \max\{B_{t+1}(x'), B_{t+1}(x')\}\frac{v_{t+1}(y')}{V_{t+1}}dy'\right] \\
&= b + \beta\,\mathrm{E}\left[(1-\lambda_{t+1})B_{t+1}(x') + \lambda_{t+1}\int B_{t+1}(x')\frac{v_{t+1}(y')}{V_{t+1}}dy'\right] \\
&= b + \beta\,\mathrm{E}\left[(1-\lambda_{t+1})B_{t+1}(x') + \lambda_{t+1}B_{t+1}(x')\right] \\
&= b + \beta\,\mathrm{E}\left[B_{t+1}(x')\right]
\end{aligned}$$

□

D.2 Joint Surplus Function

The joint surplus function is defined as the joint match value net of the unemployed worker's value, $S_t(x,y) \equiv P_t(x,y) - B_t(x)$. As mentioned in the text, the model is block recursive such that neither the distribution of firms in the economy nor the distribution of workers across matches enters the value function for the joint surplus.

Proof. First, start with the equation for the joint match value $P_t(x,y)$.

$$\begin{aligned}
P_t(x,y) = p_y + \beta\,\mathrm{E}\Big[&\big(1-(1-\delta_y)\mathbb{1}\{P_{t+1}(x',y') \geq B_{t+1}(x')\}\big)B_{t+1}(x') \\
&+ (1-\delta_y)\mathbb{1}\{P_{t+1}(x',y') \geq B_{t+1}(x')\}\Big((1-\lambda_{t+1})P_{t+1}(x',y') \\
&+ \lambda_{t+1}\int \max\{P_{t+1}(x',y'), W_{t+1}(x',y'',y')\}\frac{v_{t+1}(y'')}{V_{t+1}}\,\mathrm{d}\,y''\Big)\Big]
\end{aligned}$$

Under the wage bargaining protocol, there are two cases if an employed worker contacts another firm: either the worker moves to the poaching firm y' and receives the entire match value of the incumbent firm, or the worker stays at the incumbent firm and receives the entire match value of the poaching firm. Therefore, $W_t(x,y,y') = P_t(x,y)$. Substituting

[41] We can also see this by setting $\sigma_t = 0$ in the definition of the employed worker's value function written in terms of the surplus share: $W_t(x,y,\sigma_t) = B_t(x) + \sigma_t S_t(x,y)$. See below for more details.

this into the match value and reducing (note that the λ's cancel out) yields:

$$
\begin{aligned}
P_t(x,y) = p_y + \beta\,\mathrm{E}\Big[&\big(1-(1-\delta_y)\mathbb{1}\{P_{t+1}(x',y') \geq B_{t+1}(x')\}\big)B_{t+1}(x') \\
&+ (1-\delta_y)\mathbb{1}\{P_{t+1}(x',y') \geq B_{t+1}(x')\}P_{t+1}(x',y')\Big]
\end{aligned}
$$

Then, subtracting $B_t(x)$ from both sides (making use of the result above) yields:

$$
\begin{aligned}
P_t(x,y) - B_t(x) = p_y \quad & - b - \beta\,\mathrm{E}\Big[B_{t+1}(x')\Big] \\
& + \beta\,\mathrm{E}\Big[\big(1-(1-\delta_y)\mathbb{1}\{P_{t+1}(x',y') \geq B_{t+1}(x')\}\big)B_{t+1}(x') \\
& \qquad + (1-\delta_y)\mathbb{1}\{P_{t+1}(x',y') \geq B_{t+1}(x')\}P_{t+1}(x',y')\Big].
\end{aligned}
$$

Finally, rearranging and using the definition of the joint surplus yields the desired result.

$$
\begin{aligned}
P_t(x,y) - B_t(x) &= p_y - b + \beta\,\mathrm{E}\Big[\Big(1-(1-\delta_y)\mathbb{1}\{P_{t+1}(x',y') \geq B_{t+1}(x')\}\Big)B_{t+1}(x') \\
&\quad + (1-\delta_y)\mathbb{1}\{P_{t+1}(x',y') \geq B_{t+1}(x')\}P_{t+1}(x',y') - B_{t+1}(x')\Big] \\
&= p_y - b + (1-\delta_y)\beta\,\mathrm{E}\Big[\mathbb{1}\{P_{t+1}(x',y') \geq B_{t+1}(x')\}\Big(P_{t+1}(x',y') - B_{t+1}(x')\Big)\Big] \\
\implies S_t(x,y) &= p_y - b + (1-\delta_y)\beta\,\mathrm{E}\Big[\mathbb{1}\{S_{t+1}(x',y') \geq 0\}\Big)\Big(S_{t+1}(x',y')\Big)\Big] \\
&= p_y - b + (1-\delta_y)\beta\,\mathrm{E}\Big[\max\{S_{t+1}(x',y'), 0\}\Big]
\end{aligned}
$$

□

D.3 Deriving the Wage Equation

We can use the definition of the surplus share in Equation 9 to represent the worker's value of employment as a function of the surplus and the surplus share.

$$
W_t(x,y,\sigma_t) \equiv B_t(x) + \sigma_t S_t(x,y)
$$

From this equation, we can explicitly see that hiring from unemployment entails setting $\sigma_t = 0$. Then, if a worker employed at some firm y meets another firm y', the surplus share σ_t evolves according to the piecewise function below.

$$\sigma_t' = \begin{cases} \frac{S_t(x,y)}{S_t(x,y')} & S_t(x,y') > S_t(x,y) \\ \frac{S_t(x,y')}{S_t(x,y)} & \sigma_t S_t(x,y) < S_t(x,y') \le S_t(x,y) \\ \sigma_t & S_t(x,y') \le \sigma_t S_t(x,y) \end{cases}$$

Notice that this expression mirrors the function $R(\cdot)$ in the main text. In the first case, the worker is poached and moves to firm y', extracting the entire surplus $S_t(x, y)$ of her previous match at firm y. In the second case, the worker stays at firm y, but renegotiates her surplus share to the full amount of the surplus $S_t(x, y')$ at firm y'. In the third case, the offer is below her current surplus share and is therefore too low to trigger a renegotiation; the worker simply discards the offer and stays at firm y with the same surplus share.

Now, using the definition of the employed worker value $W_t(x, y, \sigma_t) = B_t(x)+\sigma_t S_t(x, y)$, we solve for a wage $w_t(x, y, \sigma_t)$ that implements this contract.

$$\begin{aligned} W_t(x,y,\sigma_t) &= B_t(x) + \sigma_t S_t(x,y) \\ &= w_t(x,y,\sigma_t) + \beta \operatorname{E}\Big[B_{t+1}(x')\Big] - (1-\delta_y)\beta \operatorname{E}\Big[\mathbb{1}\{S_{t+1}(x',y') \ge 0\}\Big(\\ &\qquad \lambda_{t+1} \int Q_{t+1}(x',y',\sigma_{t+1},y'') \frac{v_{t+1}(y'')}{V_{t+1}} \operatorname{d} y'' + (1-\lambda_{t+1})\sigma_{t+1} S_{t+1}(x',y')\Big)\Big] \end{aligned}$$

where $Q_t(x, y, \sigma_t, y')$ represents the surplus the worker captures due to a renegotiation:

$$Q_t(x,y,\sigma_t,y') = \begin{cases} S_t(x,y) & S_t(x,y') > S_t(x,y) \\ S_t(x,y') & \sigma_t S_t(x,y) < S_t(x,y') \le S_t(x,y) \\ \sigma_t S_t(x,y) & S_t(x,y') \le \sigma_t S_t(x,y) \end{cases}$$

Next, we can use the expression for the unemployed worker's value function to eliminate $\beta \operatorname{E}\Big[B_{t+1}(x')\Big]$ and $B_t(x)$ from the above equation. We then have

$$\begin{aligned} \sigma_t S_t(x,y) = w_t(x,y,\sigma_t) - b - (1-\delta_y)\beta \operatorname{E}\Big[\mathbb{1}\{S_{t+1}(x',y') \ge 0\}\Big(\\ \lambda_{t+1} \int Q(x',y',\sigma_{t+1},y'') \frac{v_{t+1}(y'')}{V_{t+1}} \operatorname{d} y'' + (1-\lambda_{t+1})\sigma_{t+1} S_{t+1}(x',y')\Big)\Big] \end{aligned}$$

Lastly, we substitute the definition of the surplus equation into this equation and solve for $w_t(x, y, \sigma_t)$, which yields the desired result.

$$\begin{aligned} w_t(x, y, \sigma_t) &= \sigma_t p_y + (1 - \sigma_t) b \\ &\quad - (1 - \delta_y)\beta \, \mathrm{E}\left[\mathbb{1}\{S_{t+1}(x', y') \geq 0\} \cdot \lambda_{t+1} \int R_{t+1}(x', y', \sigma_{t+1}, y'') \frac{v_{t+1}(y'')}{V_{t+1}} \, \mathrm{d}\, y''\right] \end{aligned}$$

where $R_t(x, y, \sigma_t, y') \equiv Q_t(x, y, \sigma_t, y') - \sigma_t S_t(x, y)$ is defined as below and represents the additional net surplus the worker captures due to a renegotiation:

$$R_t(x, y, \sigma_t, y') = \begin{cases} S_t(x, y) - \sigma_t S_t(x, y) & S_t(x, y') > S_t(x, y) \\ S_t(x, y') - \sigma_t S_t(x, y) & \sigma_t S_t(x, y) < S_t(x, y') \leq S_t(x, y) \\ 0 & S_t(x, y') \leq \sigma_t S_t(x, y) \end{cases}$$

D.4 Contract Distribution

Average wages by (x, y) pair are given by

$$w_t(x, y) = \int w_t(x, y, \sigma_t) g_t(x, y, \sigma_t) \, \mathrm{d}\, \sigma_t$$

where $w_t(x, y, \sigma_t)$ is the wage for a worker of age x employed at firm y with surplus share σ_t and $g_t(x, y, \sigma_t)$ is the distribution of σ's within (x, y) matches. Let $G_t(x, y, \sigma_t)$ be the cumulative distribution function corresponding to $g_t(x, y, \sigma_t)$. The contract distribution is defined similarly to the worker flow equations by the law of motion:

$$\begin{aligned} G_t(x, y, \sigma_t) = \tilde{G}_t(x, y, \sigma_t) &+ \lambda_t \int \tilde{G}_t(x, y', \sigma_t) \, \frac{v_t(y)}{V_t} \, \mathbb{1}\{\sigma_t S_t(x, y) > S_t(x, y')\} \, \mathrm{d}\, y' \\ &- \lambda_t \int \tilde{G}_t(x, y, \sigma_t) \, \frac{v_t(y')}{V_t} \, \mathbb{1}\{\sigma_t S_t(x, y) < S_t(x, y')\} \, \mathrm{d}\, y' \\ &+ \lambda_t \, \tilde{u}_t(x) \, \frac{v_t(y)}{V_t} \, \mathbb{1}\{S_t(x, y) \geq 0\} \end{aligned}$$

where $\tilde{G}_t(x', y', \sigma_t) = \Pi_{x'|x} \cdot \Pi_{y'|y} \cdot (1 - \delta_y) \cdot \mathbb{1}\{S_t(x, y) \geq 0\} \cdot G_{t-1}(x, y, \sigma_t)$.

D.5 Welfare Decompositions

$$\textit{Employment Effect}_t \approx \underbrace{\int\int e_t \, f_0^e(x, y) \, w_0(x, y) \, \mathrm{d}\, x \, \mathrm{d}\, y}_{\textit{Employment Effect: Level}} + \underbrace{\int\int e_0 \, f_t^e(x, y) \, w_0(x, y) \, \mathrm{d}\, x \, \mathrm{d}\, y}_{\textit{Employment Effect: Distribution}}$$

where e_t is total employment and $f_t^e(x, y)$ is the distribution of employment across matches (x, y). The *Employment Effect: Level* shows the effect of the change in employment, holding the match distribution constant and the *Employment Effect: Distribution* shows the effect of the change in sorting patterns, holding the employment level constant.

$$\textit{Wage Effect}_t \approx \underbrace{\int\int e_0 f_0^e(x,y) \int w_t(x,y,\sigma) g_0(x,y,\sigma)\,\mathrm{d}\,\sigma\,\mathrm{d}\,x\,\mathrm{d}\,y}_{\textit{Wage Effect: Level}} + \underbrace{\int\int e_0 f_0^e(x,y) \int w_0(x,y,\sigma) g_t(x,y,\sigma)\,\mathrm{d}\,\sigma\,\mathrm{d}\,x\,\mathrm{d}\,y}_{\textit{Wage Effect: Distribution}}$$

where $w_t(x,y,\sigma)$ is the level of and $g_t(x,y,\sigma)$ is the distribution of within-match wages across surplus shares. The *Wage Effect: Level* (*Distribution*) allows $w_t(x,y,\sigma)$ ($g_t(x,y,\sigma)$) to vary, holding $g_t(x,y,\sigma)$ ($w_t(x,y,\sigma)$) constant.

E Additional Model Details

The transition matrices for worker age bin and firm age bin are given by the following expressions. Note that the model is set to monthly frequency.

$$\Pi_{x'|x} = \begin{bmatrix} 1-\frac{1}{120} & \frac{1}{120} & 0 & 0 \\ 0 & 1-\frac{1}{120} & \frac{1}{120} & 0 \\ 0 & 0 & 1-\frac{1}{120} & \frac{1}{120} \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad \Pi_{y'|y} = \begin{bmatrix} 1-\frac{1}{24} & \frac{1}{24} & 0 & 0 & 0 \\ 0 & 1-\frac{1}{24} & \frac{1}{24} & 0 & 0 \\ 0 & 0 & 1-\frac{1}{24} & \frac{1}{24} & 0 \\ 0 & 0 & 0 & 1-\frac{1}{60} & \frac{1}{60} \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

E.1 Model Solution

I use standard numerical techniques to solve the value function for the joint match surplus and to find the employment distribution in steady state. Given values for p_y, b, and δ_y, I first solve for the joint surplus function (Equation 2) by value function iteration. Then, I iterate on the worker flow equations (Equations 7 and 8) in order to solve for the steady state worker distribution, starting from an initial guess where all workers are unemployed. Each step of the iteration requires solving for aggregate search intensity (Equation 3), the value of a filled vacancy (Equation 4), and aggregate vacancies (Equation 6) in order to pin down the contact rates λ_t and μ_t. This also determines the vacancy distribution across firm ages $\frac{v_t(y)}{V_t}$. Next, I solve for wages at the match level by first using Equation 10 to obtain the wage $w_t(x,y,\sigma_t)$ for any pair (x,y) and any possible surplus share $\sigma_t = \sigma_t(x, y, y')$; then, I iterate on the law of motion for the distribution of contracts across σ_t within an (x, y) pair. This allows me to compute average wages by (x, y) pair. Appendix D.4 shows the law of motion for the distribution of wage contracts. With few worker and firm age bins, the entire solution algorithm converges very quickly.

E.2 Model Estimation

Let $m(\theta)$ denote a vector of steady state model moments under θ. Let $\hat{m}$ denote the vector of corresponding data moments. Both $m(\theta)$ and $\hat{m}$ are $N \times 1$ vectors, where $N = 11$. I choose parameter vector $\hat{\theta}$ in order to minimize the objective function:

$$\hat{\theta} = \arg\min_{\theta} \sqrt{\frac{1}{N} \sum_{i=1}^{N} \left(\frac{m_i(\theta) - \hat{m}_i}{\hat{m}_i} \right)^2}$$

where i indexes moments. The objective function value is interpreted in terms of percent differences. For instance, an objective function value of 0.10 means that the average deviation between model and data moments is 10 percent. The advantage of this functional form is that it properly weights across moments that are expressed in different units.

Global Optimization Algorithm The parameter space is fairly large and the objective function is nonsmooth, so I use global methods to find the parameters that minimize the distance between the model and data moments. I first select a set of candidate solutions and then run a local minimizer from each of these starting values. The algorithm is below.

1. Select $S = 250,000$ candidate starting points using Sobol sequences. Evaluate the objective function at each of these points and store the results in a vector. Keep the best (i.e. lowest function value) $S^* = 1,000$ of these points.

2. Run a local optimization routine (Nelder-Mead algorithm) starting from each of these S^* points and store the resulting function values and parameter vectors.

   (a) Let f^* denote the $1 \times S^*$ vector of objective function values at the local optima corresponding to the S^* starting points.

   (b) Let θ^* denote the $N \times S^*$ matrix of parameter values at the local optima corresponding to the S^* starting points.

3. Find the lowest function value among f^* and call this $\hat{f}$; find the parameter vector in θ^* that corresponds to $\hat{f}$. Let $\hat{\theta}$ denote the parameter vector that corresponds to $\hat{f}$. $\hat{\theta}$ is the global minimum.

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