Declining Business Dynamism and Worker Mobility*

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Abstract

The firm entry rate in the United States declined in recent decades, leading to an increase in the share of older, larger businesses. Younger workers tend to sort into younger firms, suggesting that the fall in the startup firm share differentially impacted labor market outcomes across the worker life-cycle. To assess this hypothesis and to quantify the consequences of the decline in firm entry for workers' careers, I develop an equilibrium labor market sorting model featuring both on-the-job search and two-sided, life-cycle heterogeneity. I find that firm aging alone accounts for about two-thirds of the decline in the aggregate employer switching rate and about one-fifth of the decline in the aggregate employment-to-population ratio between 1994 and 2019. Aggregate worker welfare falls by about 0.7 percent along the transition path, with younger workers experiencing larger declines.

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JEL Classification: E24, L26, J62, M13

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1 Introduction

Over the past several decades, the United States economy experienced a dramatic decline in business dynamism. Firm entry and exit rates decreased, increasing the proportion of larger, older businesses in the economy. Moreover, despite large secular changes in economic activity over this time horizon, these trends were pervasive across regions and industries.[1] In this paper, I investigate the implications of declining business dynamism for aggregate labor market outcomes as well as labor market outcomes across older and younger groups of workers.

My analysis begins with the observation that the age composition of employment changes across the firm life-cycle. Using data from the U.S. Census Bureau's Quarterly Workforce Indicators (QWI) database, I show that while more mature firms (11 years and older) employ younger and older workers in proportion with their representation in the labor force, the age composition of employment at younger firms is significantly skewed towards younger workers.[2] This finding is not accounted for by differences in firm size across firm age categories, is not driven by certain sectors or regions, and has remained stable over time. The fact that younger workers differentially sort into younger firms suggests 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 labor market effects of the declining share of young firms, I develop an equilibrium model of labor market sorting between heterogeneous workers and heterogeneous firms with on-the-job search (OJS). Into an otherwise standard labor market sorting model, I introduce a life-cycle for both firms and workers as well as a time varying firm age distribution, which changes in response to innovations in the rate at which firms enter and exit the economy.[3] 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 consequences of changes in the firm entry rate for labor market outcomes across cohorts of workers. Through the lens of the model, the decline in the firm entry rate accounts for a significant share of the decline in the employer switching rate since the 1990s both on 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).

In the model, both workers and firms differ by their current stage of the life-cycle.

[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 locations.
[2] Ouimet and Zarutskie (2014) also document this pattern using Census microdata for the years 1992–2004.
[3] I extend the framework of Lise and Robin (2017), introducing both worker and firm heterogeneity by age.

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 careers 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 a flow wage that depends on their current match and stage of the life-cycle.

Wages are set according to sequential auctions bargaining (Postel-Vinay and Robin, 2002).[4] As in Lise and Robin (2017), workers hired out of unemployment have no bargaining power such that the hiring firm offers the worker her reservation value and extracts the entire match surplus. Jointly, these assumptions deliver tractability and enable me to estimate the model to match key moments in the data.

I choose 1994 as the starting point for my analysis and estimate the model in steady state to match several features of the firm life-cycle in the cross-section.[5] The calibration strategy allows firms to differ across the life-cycle along three key dimensions. First, young firms have higher separation rates, reflecting their higher rates of turnover and lower rates of survival in the data. Second, firm productivity evolves over the life-cycle according to a simple, reduced form expression for match-level output that I calibrate to match the wage profile by firm age. I find that older firms are larger and more productive, reflecting either selection or growth effects. Third, average and marginal vacancy posting costs vary across the firm life-cycle. I calibrate 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 vs. old firms.

The model reproduces these features of the firm life-cycle quite well. Additionally, though I do not target them in my moment matching exercise, the model matches other important features of both the firm and worker life-cycle. First, the model captures the relative ranking of young vs. 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 composed of

[4] I 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.

[5] I choose this time period 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).

younger workers. Last, the model matches the life-cycle profile of worker separations and job-to-job flows, which are both decreasing in age, and wages, which are increasing in age. These patterns stem from a composition effect: older workers are sorted into older firms that have lower turnover rates and pay higher wages. That the model reproduces them to some degree speaks to the importance of the job ladder for life-cycle dynamics.[6]

With the estimated model in hand, I then explore the implications of the decline in the firm entry rate for labor market outcomes. Starting from the initial steady state, I simulate a decline in business dynamism by allowing the firm age distribution and total number of firms in the economy to evolve in a manner consistent with the data. In the data, firm exit rates conditional on firm age group have remained roughly stable since 1994, but the firm entry rate has dropped precipitously. Therefore, both the share of young firms and the number of firms per worker in the economy have declined over this time period. I calibrate the law of motion for the mass of firms by firm age group to match these patterns. I then feed this law of motion into the model and study the evolution of the economy along the transition path.

I find that through the lens of the model, the change in the firm age distribution 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 searching for jobs and firms posting vacancies falls, leading to a drop in the contact rate. The aggregate job finding rate declines by 4 percentage points (15 %), the aggregate job-to-job switching rate declines by 0.20 percentage points (20 %), and the aggregate job separation rate stays roughly constant. Because job finding falls more than job separation, the employment rate falls (nonemployment rate rises) by about 0.9 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 calibrated 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 due to the fall in the con-

[6]Importantly, I include only *cross-sectional* moments related to the firm life-cycle in my calibration strategy. This approach also guides the quantitative experiment I pursue: take firm dynamics as given and study their implications for workers by age group.

tact rate combined with their higher average search intensity.

Taking these predictions to the data, I find that the decline in business dynamism accounts for about 67 percent of the decline in the aggregate employer switching rate and about 20 percent of the decline in the aggregate employment-to-population ratio between 1994 and 2019. Notably, the decline in business dynamism also accounts for the fact that worker mobility has fallen by more for 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.

My baseline analysis holds the worker distribution constant at the initial steady state. However, demographic change over this time horizon could have also produced a decline in aggregate employer switching either mechanically or through its effects on firm entry and reallocation (Engbom, 2019; Hopenhayn et al., 2022; Karahan et al., 2024). To simulate the combined effects of declining firm entry and workforce aging, I conduct an additional experiment whereby I allow both the firm and worker distributions to evolve as in the data. I perform a shift-share analysis to formally decompose aggregate changes in the employer switching rate into components that capture only (i) changes in age-group-specific employer switching rates, holding labor force composition constant and (ii) changes in labor force composition, holding age-group-specific employer switching rates constant. I apply this analysis both to data on employer switching from the Current Population Survey (CPS) and to the model simulated trends. 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 in order 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 the calibration exercise finds are more productive, increases, the average match in the economy is of higher quality. I refer to the first channel as the "match-level effect" and to the second channel as the "match-distribution effect."

I find that quantitatively, the match-level effect dominates, and workers experience an overall decline in welfare of about 0.7 percent. Though the employment distribution shifts towards 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 decline in their bargaining power. 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 studies the causes and consequences of the recent decline in business dynamism. The literature that examines the causes of declining business dynamism is too large to catalog extensively.[7] However, I highlight two recent papers that document empirical evidence that motivates my analysis. Both Hopenhayn et al. (2022) and Karahan et al. (2024) find that firm dynamics within cohorts of firms have remained stable in recent decades. Therefore, the changing composition of firms by firm age, in turn driven by a decline in the firm entry rate, entirely accounts for any observed aggregate trends in firm dynamics such as the firm exit rate, average firm size, and concentration. They show that in firm dynamics models with linear entry conditions based on Hopenhayn (1992), a decline in labor supply growth produces trends consistent with these empirical patterns. In this paper, I additionally examine the implications of trends in business dynamism for labor market outcomes and inequality across worker cohorts.

My study connects to several papers that consider the life-cycle dimension 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, young workers earn higher wages in young firms, and talented young workers select into young firms that display higher innovation and growth potential. Haltiwanger

[7] See Decker et al. (2016) as well as Ackcigit and Ates (2021, 2023) for an overview of the literature.

et al. (2018b) show that business cycles disproportionately affect job ladder dynamics for younger and less educated workers. 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 analysis, life-cycle sorting patterns of employment form the basis through which a decline in the share of young firms differentially affects job mobility rates for young vs. old workers.

Next, this paper builds on work in Postel-Vinay and Robin (2002), Lise and Robin (2017), and Lentz et al. (2017), who develop models of two-sided heterogeneity and labor market sorting. In these studies, 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 dimension of worker mobility and labor market sorting, but also to speak to differential changes in labor market outcomes across different cohorts of workers.

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 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. Bilal et al. (2022) and Elsby and Gottfries (2022) build tractable firm dynamics models with frictional labor markets, on-the-job search, and decreasing returns to scale in production. I develop a method to include life-cycle dimensions for both worker and firm outcomes while also maintaining analytical tractability under a related set of assumptions on the production and vacancy posting cost functions.[8] While both papers focus on the business cycle dimension of worker flows, I study the long-term decline in business dynamism.

Finally, my paper relates to studies that propose explanations for the declining trend in worker mobility.[9] 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

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

[9] 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.

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 calibration strategy of the model. Section 5 explores the effects of a decline in business dynamism on the economy and compares the model's predictions to the data. Section 6 discusses the welfare implications of declining business dynamism in the aggregate and across worker cohorts. Section 7 concludes.

2 Motivating Evidence

In this section, I present motivating evidence on trends in firm dynamics and on the age distribution of employment across 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 towards younger workers. I describe the data sources in Online Appendix A and the methodology below.

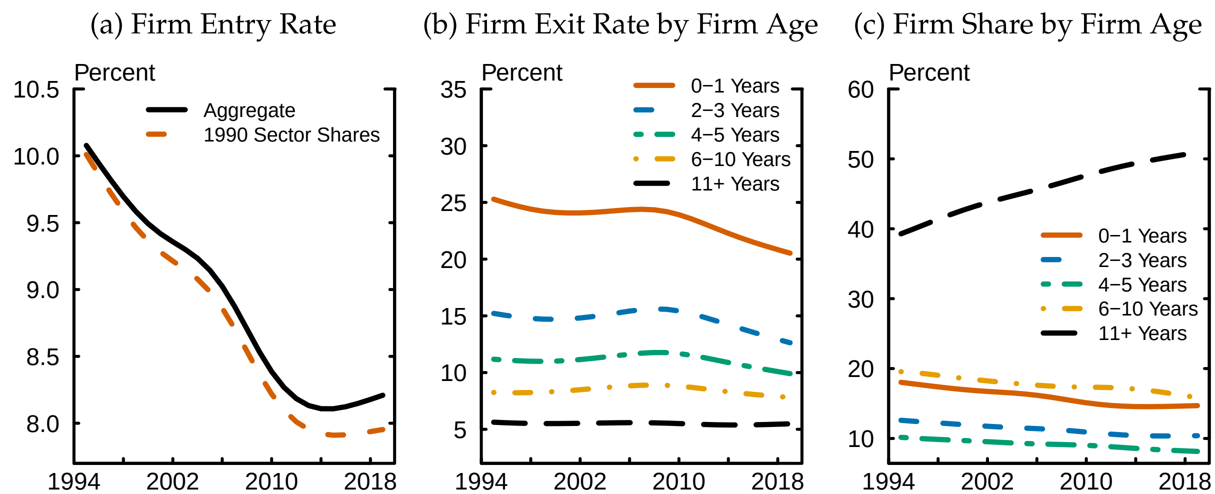
2.1 Decline in Firm Entry and Shift of Firm Age Distribution

Figure 1 displays trends in various measures of firm dynamics from 1994 to 2019.[10] 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 towards older firms. Moreover, the decline in the firm entry rate was a pervasive phenomenon across markets (Decker et al., 2014; Pugsley and Şahin, 2019).[11] 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 survival and growth rates do not display large trends within firm age groups (panel 1b).

[10] 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).

[11] See Online 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 Online Appendix A.

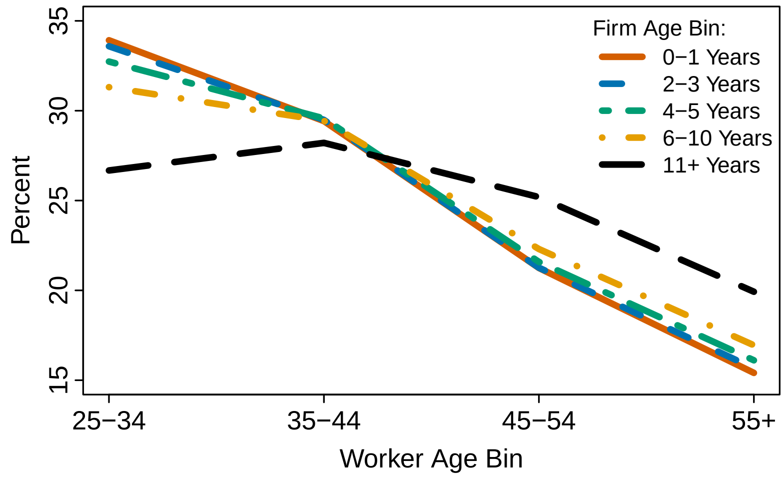
Given the stability of firm dynamics conditional on firm age, it must be the case that the changing composition of firms by firm age resulted exclusively from changes in the entry margin (panel 1c). Therefore, any observed *aggregate* trends in firm exit rates, growth rates, average firm size, and concentration are all driven by changes in the firm age distribution, induced by a decline in the number of new startup firms created each year. Even more remarkable is that 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 Worker and Firm Life-Cycle Sorting Patterns

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 towards younger workers. That is, younger firms tend to employ younger workers in higher proportions.

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

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 Online Appendix A.

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 towards 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

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

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 state j and industry k during year t.[12] 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 state $\times$ industry $\times$ year cell. I include fixed effects at the state, 4-digit NAICS industry, and year level to allow 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 as well as controls for employment composition across different levels of educational attainment. This is because the observed pattern of sorting on age could instead reflect sorting on worker and

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

Table 1: Worker and Firm Sorting Patterns by Firm Age

	(1)	(2)	(3)	(4)
Firm Age 0–10 Years	14.729***	15.086***	14.892***	14.443***
	(0.038)	(0.037)	(0.033)	(0.113)
Frac. Educ. $\leq$ High School				0.160***
				(0.002)
ln(Avg. Firm Size)				1.739***
				(0.049)
Firm Age 0–10 Years $\times$ ln(Avg. Firm Size)				−0.355***
				(0.045)
Year Fixed Effects	X	X	X	X
State Fixed Effects		X	X	X
Industry Fixed Effects			X	X
Observations	464,606	464,606	464,606	367,033
R^2	0.332	0.356	0.529	0.593

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. Industry fixed effects are at the 4-digit NAICS level. Standard errors in parentheses. $^{*}p \leq 0.10$;$^{**}\, p \leq 0.05$;$^{***}\, p \leq 0.01$.

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 significantly higher proportion of young workers. Being a firm in the 0–10 year old age category is associated with having an employment composition of age $<$ 45 year old workers approximately 15 percentage points higher relative to firms in the 11+ age category.[13] 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.[14] If anything, increases in average firm size are associated with having a *higher* proportion of young workers, and this association is weaker for firms in the 0–10 year old age category.

Ouimet and Zarutskie (2014) document a similar pattern using microdata from the Census Bureau for the period 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 groups and education groups and discuss the

[13]Note that these magnitudes are 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. Online Appendix B shows the employment distribution across worker age group by firm age group using the state $\times$ industry $\times$ year data.

[14]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., 2018a; Bilal et al., 2022).

results in Online Appendix C. I do not find that potential sorting along these dimensions masks sorting on worker and firm age, and conclude that there is an important life-cycle component to labor market sorting.

3 Model of Worker and Firm 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 documented above, I abstract from worker and firm heterogeneity other than in age. Wages are set according to sequential auctions bargaining as in Postel-Vinay and Robin (2002). Below, I elaborate on the model structure and the wage setting protocol; I relegate explicit derivations of key equations to Online Appendix D.

3.1 Environment

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

The density of workers by age is given by $\ell_t(x)$ with mass $\mathcal{L}_t$, normalized to 1 in steady state. Workers enter the economy into the youngest age group at rate η_t and exit the labor force due to retirement at rate ω_x, which depends on their age x. The density of firms by age at time t is given by $m_t(y)$ with mass $\mathcal{M}_t$. Firms enter the economy into the youngest age group at rate γ_t and exit at rate $\zeta_{y,t}$, which depends on their age y. To keep the state space manageable, workers and firms age stochastically according to the Markov processes $\Pi_{x'|x}$ and $\Pi_{y'|y}$, respectively.[15]

Workers are either employed or unemployed. A worker of age x employed at a firm of age y produces flow match output $p_{x,y}$. The worker earns a flow wage of $w_t(x, y)$, which is the equilibrium outcome of a sequential auctions bargaining procedure outlined below. A worker of age x receives flow nonemployment benefit b_x while unemployed.

Both employed and unemployed workers may search for jobs, so the model features on-the-job search (OJS). The contact rate for workers λ_t is determined by a constant returns to scale matching function, defined below. Further, worker search intensity ϕ_x^i is set exogenously and depends on both worker age x and employment status $i \in \{\text{employed } (e), \text{unemployed } (u)\}$. An employed worker of age x contacts a firm at rate $\phi_x^e \lambda_t$ and an unemployed worker of age x contacts a firm at rate $\phi_x^u \lambda_t$.

[15] In the quantification of the model, I choose age categories consistent with the age bins available in the data.

Timing Within each period, there are two stages. At the beginning of the period, a certain fraction of employed 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 both worker and firm age changes according to $\Pi_{x'|x}$ and $\Pi_{y'|y}$, respectively. The workers who exited the labor force are replaced by new labor market entrants in the youngest age group, 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

The value function for an unemployed worker of age x is given below.

$$\begin{aligned} W_t^u(x) = b_x + (1-\omega_x)\beta\,\mathrm{E}_{x'}\Big[&(1-\phi_x^u\lambda_{t+1})W_{t+1}^u(x') \\ &+ \phi_x^u\lambda_{t+1}\int \max\{W_{t+1}^e(x',y'), W_{t+1}^u(x')\}\frac{v_{t+1}(y')}{V_{t+1}}dy'|x\Big] \end{aligned}$$

While unemployed, a worker receives flow nonemployment benefit b_x. If she does not retire, she stays in the labor market and searches for jobs in the next period. With probability $(1-\phi_x^u\lambda_{t+1})$ she fails to contact a firm and remains unemployed, possibly with new age x'. With complementary probability $\phi_x^u\lambda_{t+1}$ she contacts a firm and receives the employed worker value $W_{t+1}^e(x',y')$, provided that it is greater than the continuation value of unemployment. Otherwise, she remains unemployed.

Conditional on contacting a firm, the worker forms a match with a firm of age y' with probability $\frac{v_{t+1}(y')}{V_{t+1}}$, where $v_t(y)$ is the number of vacancies posted by firms of age y and $V_t = \int v_t(y)\,\mathrm{d}\,y$ is the total number of vacancies in the economy. Therefore, $\frac{v_t(y)}{V_t}$ is the density of vacancies posted by firms of age y.

Following Lise and Robin (2017), unemployed workers have zero bargaining power so that workers hired out of unemployment are offered their reservation value, $W_t^e(x,y) = W_t^u(x)$. Hence, the unemployed worker's value function reduces to the equation below.

$$W_t^u(x) = b_x + (1-\omega_x)\beta\,\mathrm{E}_{x'}\Big[W_{t+1}^u(x')|x\Big] \tag{1}$$

This expression states that the value of unemployment is simply the present discounted value of current and future flow nonemployment benefits b_x, which represents any per-period utility value a worker receives while unemployed. In particular, it may stand for home production, leisure value, or explicit unemployment benefit payments. It may also vary by worker age. Though the assumption above implies that workers are technically indifferent between unemployment and employment, I follow Lise and Robin (2017) and assume that unemployed workers always accept job offers.

The value function for employed workers $W_t^e(x, y)$ is not specified 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 with flow output $p_{x,y}$. In other words, $P_t(x, y)$ represents the value of a match between a worker of age x and a firm of age y. The value function for $P_t(x, y)$ is given below.

$$
\begin{aligned}
P_t(x,y) = p_{x,y} & \\
& + (1-\omega_x)\beta\, \mathrm{E}_{x',y'}\Big[\big(1-(1-\delta_{x,y})\mathbb{1}\{P_{t+1}(x',y') \geq W^u_{t+1}(x')\}\big)W^u_{t+1}(x') \\
& \qquad + (1-\delta_{x,y})\mathbb{1}\{P_{t+1}(x',y') \geq W^u_{t+1}(x')\}\Big((1-\phi^e_x\lambda_{t+1})P_{t+1}(x',y') \\
& \qquad\quad + \phi^e_x\lambda_{t+1}\int \max\{P_{t+1}(x',y'), W^e_{t+1}(x',y'',y')\}\frac{v_{t+1}(y'')}{V_{t+1}}\,\mathrm{d}\,y''\Big) \,|\, x,y\Big]
\end{aligned}
$$

In the current period, a match between a worker of age x and a firm of age y produces $p_{x,y}$. Assuming the worker does not retire, the match dissolves exogenously with probability $\delta_{x,y}$, which may depend on both worker age and firm age. A match dissolves endogenously if, after firms and workers learn their new ages, the continuation value of the match drops below the value of the worker's outside option, $P_{t+1}(x', y') < W^u_{t+1}(x')$. Instead, if the match persists, the employed worker has the opportunity to meet a new firm of age y'' with probability $\phi^e_x\lambda_{t+1}\frac{v_{t+1}(y'')}{V_{t+1}}$. If she fails to meet a new firm, the match persists with the same continuation value. However, if an employed worker successfully meets a new firm, then the incumbent firm and the poaching firm enter into Bertrand competition over the worker's services. This procedure follows Postel-Vinay and Robin (2002) and is explained in more detail below.[16]

3.3 Sequential Auctions Protocol

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

[16]Many of the features below are standard in labor market sorting models. Therefore, I include additional details and explicit derivations in Online Appendix D.

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 firm. As a result, the continuation value of the match is independent of whether or not the worker is poached and therefore of the employed worker value function $W_t^e(x,y,y')$.

Joint Surplus Instead, we may write the joint worker and firm problem in terms of the joint surplus of the match. Let $S_t(x,y) = P_t(x,y) - W_t^u(x)$ 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.

$$S_t(x,y) = p_{x,y} - b_x + (1-\omega_x)(1-\delta_{x,y})\beta\, \mathrm{E}_{x',y'}\left[\max\{S_{t+1}(x',y'),0\} \,|\, x,y\right] \tag{2}$$

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 nonemployment, plus expected future surplus if the match continues. Given flow match output $p_{x,y}$ and flow nonemployment value b_x, solving Equation 2 determines the surplus value of any possible match in the economy, simplifying the equilibrium computation considerably.[17]

3.4 Worker Search and Vacancy Posting

Let $\tilde{u}_t(x)$ and $\tilde{e}_t(x,y)$ represent the stock of unemployed and employed workers, respectively, after the separation stage. These objects are determined below. Aggregate search intensity L_t is composed of the stocks of unemployed and employed workers that prevail after the separation stage, scaled by their respective individual search intensities.

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

Knowing aggregate search intensity, firms post vacancies in order to hire workers from the pool of total searchers. The expected value of meeting a worker for a firm of age

[17]Notice that the distribution of employment does not appear in this equation, meaning that the model has the block-recursive property, as shown in Lise and Robin (2017). Block-recursivity stems from the assumption that unemployed workers have no bargaining power along with the fact that the sequential auctions protocol renders the match continuation value independent of the employed worker value.

y is given by the expression below.

$$J_t(y) = \int \frac{\phi_x^u \tilde{u}_t(x)}{L_t} \max\{S_t(x,y), 0\} \,\mathrm{d}\, x + \int\int \frac{\phi_x^e \tilde{e}_t(x,y')}{L_t} \max\{S_t(x,y) - S_t(x,y'), 0\} \,\mathrm{d}\, x \,\mathrm{d}\, y' \tag{4}$$

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 expected value of a filled vacancy is equal to the marginal cost of opening a 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.

Matching and Contact Rates Meetings between the masses of searching workers L_t and firm vacancies V_t are produced according to a constant returns to scale matching function $\Psi(L_t, V_t)$. The rate at which workers contact firms depends on both worker search intensity ϕ_x^i and the aggregate probability of meeting a firm $\lambda_t \equiv \frac{\Psi(L_t,V_t)}{L_t}$. Hence, the contact rate for workers is given by $\phi_x^u \lambda_t = \phi_x^u \frac{\Psi(L_t,V_t)}{L_t}$, which depends on both their labor market status and their age. The rate at which firms contact workers is given by $\mu_t \equiv \frac{\Psi(L_t,V_t)}{V_t}$.

Worker Flow Equations Given the surplus function $S_t(x,y)$, total search effort L_t and vacancies V_t, as well as the masses of unemployed and employed searchers after the sep-

[18]Notice both that if $S_t(x,y) < 0$ the match is not formed and that no firm may poach a worker from another firm with a higher surplus.

aration stage, $\tilde{u}_t(x)$ and $\tilde{e}_t(x, y)$, respectively, the laws of motion below determine the masses of employed and unemployed workers at the end of the period.

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

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

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. Note that each of these components is weighted by $\frac{v_t(y)}{V_t}$, the share of total vacancies at firms of age y.

Additionally, the objects $\tilde{u}_t(x)$ and $\tilde{e}_t(x, y)$ are determined as follows.

$$\begin{aligned} \tilde{u}_t(x') = & \, \Pi_{x'|x} \cdot (1 - \omega_x) \left[u_t(x) + \int \big(\mathbb{1}\{S_t(x, y) < 0\} + \delta_{x,y} \cdot \mathbb{1}\{S_t(x, y) \geq 0\}\big) \cdot e_{t-1}(x, y) \, \mathrm{d}\, y\right] \\ & + \eta_t \cdot \mathbb{1}\{x' = \underline{x}\} \end{aligned}$$

This expression states that the number of unemployed workers of age x' after the separation stage 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 $\underline{x}$. 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. Lastly,

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

This expression states that the number of employed workers of age x' at firms of age y' after the separation stage consists of workers already employed at these firms who survive job destruction and retirement.

3.5 Wage Setting

To pin down wages, I follow Lentz et al. (2017) and assume that firms commit to deliver a constant share σ_t of the surplus for the entire duration of a match until and unless the worker receives an outside offer. The worker receives a share $\sigma_t(x, y, y')$ of the surplus that depends on her age x, her current firm y, and her previous firm (previous outside offer) y'. In particular, for $S_t(x, y) \geq S_t(x, y')$,

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

This assumption is convenient because it produces a closed form solution for the wage equation. Wages evolve according to the equation:

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

where the term $R_t(x, y, \sigma_t, y')$ captures the possible outcomes of the sequential auctions protocol and represents the additional surplus the worker captures due to renegotiation.[19] The wage is a weighted average of flow match output $p_{x,y}$ and flow nonemployment benefit b_x, net of future expected renegotiation opportunities captured by the final term in Equation 10 containing $R_t(x, y, \sigma_t, y')$. As a result of this term, wages will be lower for lower tenure workers, as these workers expect to have future opportunities to climb the job ladder and renegotiate their wages upward.

3.6 Laws of Motion for Workers and Firms

The law of motion for the mass of workers of age x' in time period t is as follows:

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

[19] See Online Appendix D for the explicit expression of $R_t(x, y, \sigma_t, y')$.

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 group $\underline{x}$). Note that in steady state, the masses of entering and retiring workers are equivalent; I also normalize the total mass of workers in steady state to 1 so that $\int \bar{\ell}(x)\, \mathrm{d}\, x = 1$ for the steady state mass of workers by age $\bar{\ell}(x)$.

Similarly, the law of motion for the mass of firms of age y' in time period t is:

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

where $\Pi_{y'|y}$ is the transition matrix across firm age bins, $\zeta_{y,t}$ is the exit rate for firm age y at time t, and γ_t is the entry rate of firms into the lowest firm age $\underline{y}$. Given exit rates $\zeta_{y,t}$ and entry rate γ_t, the steady state mass of firms by firm age, which I denote $\bar{m}(y)$, is the fixed point of Equation 12. The total mass of firms in the economy is given by $\mathcal{M}_t \equiv \int m_t(y)\, \mathrm{d}\, y$. The normalization I make to the worker distribution implies that the interpretation of $\mathcal{M}_t$ is the number of firms-per-worker at time t.

4 Numerical Implementation and Calibration

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

4.1 Worker and Firm Age Bins

I define the model at the bin-level and choose the same bins as in the Census Bureau data used in Section 2. There are 4 worker age bins $\{25\text{–}34, 35\text{–}44, 45\text{–}54, 55+\}$ and 5 firm age bins $\{0\text{–}1, 2\text{–}3, 4\text{–}5, 6\text{–}10, 11+\}$, 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.

[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 Online Appendix E.

4.2 Functional Form Assumptions

I assume the matching function $\Psi(L_t, V_t)$ is Cobb–Douglas with elasticity parameter α.

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

I normalize aggregate matching efficiency to 1. Hence, the contact rate for an unemployed worker of age x is given by $\phi_x^u \lambda_t = \phi_x^u \frac{\Psi(L_t,V_t)}{L_t} = \phi_x^u \left(\frac{V_t}{L_t}\right)^{1-\alpha}$ and the contact rate for an employed worker of age x is given by $\phi_x^e \lambda_t = \phi_x^e \frac{\Psi(L_t,V_t)}{L_t} = \phi_x^e \left(\frac{V_t}{L_t}\right)^{1-\alpha}$.

Worker search intensity ϕ_x^i is set exogenously and depends on both worker age x and employment status $i \in \{\text{employed } (e), \text{unemployed } (u)\}$. I assume that the labor market status component of search intensity, which I denote by κ_i, and the worker age component, which I denote by ψ_x, enter multiplicatively, so that $\phi_x^i = \kappa_i \cdot \psi_x$.

I parameterize the vacancy posting 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.

Worker Flow Values In my baseline calibration, I suppress the dependence of match-level output on worker age so that $p_{x,y} = p_y$. I assume 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 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 follow Lise and Robin (2017) and set the flow nonemployment benefit b_x such that it is equal to some fraction b_0 of a worker's maximum attainable match output.

$$b_x = b_0 \cdot \max_y \{p_y\}$$

In the expression above, $\max_y\{p_y\}$ stands for the match output at worker x's most productive match. The assumption of no differences in match output p_y across workers within firms implies that the flow benefit $b_x = b$ is the same across worker ages.

4.3 Calibration

Table 2 shows the calibrated parameters. I assume that the economy is in steady state in 1994 and calibrate 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 matching 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 vs. unemployed workers (Faberman et al., 2022).[21]

Directly Estimated Parameters The retirement rate is set such that workers only face retirement once they enter the oldest age bin (55+). I set the retirement rate for this age bin so as to match the share of workers age 55 and over in the labor force in 1990–1994.[22]

I set the search intensity by age group parameters ψ_x to target the age profile of the job finding rate in 1990–1994. Workers in the youngest age group (25–34) have the highest job finding rates, so I normalize their search intensity to 1. The ψ_x's for all other age groups are set relative to the youngest worker age group (25–34). They are calculated by taking the ratio of the job finding rate for age group x to the job finding rate for age group 25–34.

I assume that the exogenous separation rate $\delta_{x,y}$ varies only by firm age such that $\delta_{x,y} = \delta_y$. I then set δ_y directly to the value of the job destruction rate by firm age group from the BDS in 1990–1994. 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 with a firm age bin are undefined. The separation rate δ_y includes both cases:

[21] See Baley et al. (2022) for a similar implementation of this calibration strategy for worker search intensity.
[22] For this moment and the moments that follow, I take averages over this period.

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	Matching 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	0.147	0.147
ψ_x	Search intensity by worker age bin	25–34	1.000	Job finding rate by worker age bin	0.293	0.289
		35–44	0.899		0.263	0.259
		45–54	0.822		0.241	0.237
		55+	0.683		0.200	0.197
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	–	0.219	Job finding rate	0.264	0.254
c_1	c_y slope parameter	–	1.144	Average firm size	See Figure 3	
c_2	c_y curvature parameter	–	2.055	by firm age bin	See Figure 3	
p_0	p_y level parameter	–	2.089		See Figure 3	
p_1	p_y slope parameter	–	0.444	Average earnings	See Figure 3	
p_2	p_y curvature parameter	–	-0.194	by firm age bin	See Figure 3	
b_0	b scale parameter	–	0.847		See Figure 3	

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

employees leaving a firm that survives as well as employees returning to unemployment because their firm has closed down.

I set the steady-state mass of firms by firm age bin $\bar{m}(y)$ directly to its empirical value. I calculate this value for each firm age bin by taking the ratio of the number of firms in that age bin to the total number of workers in the labor force, HP-filtering the resulting series with an annual smoothing parameter, and extracting the value in 1994.

Internally Estimated Parameters I calibrate the parameters that govern the vacancy cost level c_y, match-level output p_y, and flow nonemployment value b so that the steady state of the model matches several moments in the data. In particular, I target the aggregate job finding rate, average firm size by firm age, and average earnings by firm age. The data moments are taken as time averages over the period 1990–1994; Online Appendix F contains additional details on moment construction. In total, I calibrate 7 parameters to match 11 bin-level moments in the data, meaning that the model is overidentified. The parameter vector is $\theta = \{c_0, c_1, c_2, p_0, p_1, p_2, b_0\}$.

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 may be 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. I use global methods to efficiently and thoroughly search the parameter space.[23]

Though the parameters in my moment matching exercise are jointly identified by the moments in the data, it is useful to consider which moments in particular are informative about specific parameters. The parameters in the vacancy cost function pin down both average firm size across firms and 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 the level of vacancy costs c_y shifts up or down the number of vacancies posted by firms of each age. Therefore, appropriately setting the parameters (c_0, c_1, c_2) pins down the vacancy distribution as well as 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, the match-level output function p_y and the flow nonemployment benefit b both

[23] Online Appendix F contains a detailed description of the global minimization algorithm.

[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 $v_t(y)$.

enter directly into the wage equation, which I reproduce below.[25] They also affect wages indirectly through the "Expected Renegotiation Benefit" term, as they affect the shape of the surplus function $S(x, y)$. This term 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.

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

Therefore, the parameters of the match-level output function primarily determine the shape of the wage profile across firm age bins. The scaling parameter b_0 also helps control the overall level of wages. In the model, if unemployment becomes "too costly" – i.e. b is very low relative to p_y – then workers accept wages that are counterfactually too low (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 to keep the model tractable. However, setting b_0 sufficiently high mitigates this effect so that wages remain positive.

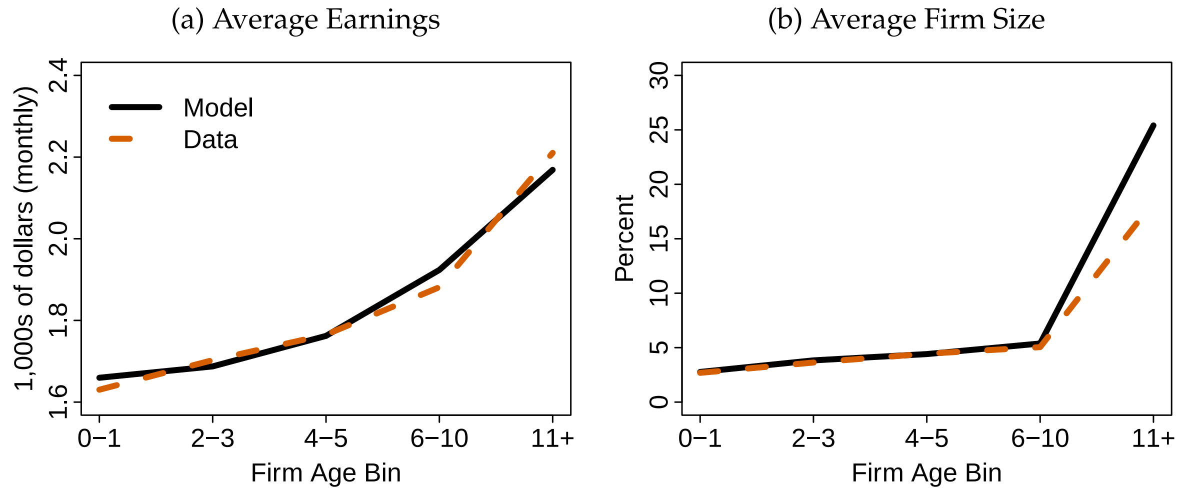
Model Fit The last two columns of Table 2 compare the model implied moments to their counterparts in the data. First, the job finding rate is slightly underestimated at roughly 25% in the model vs. 26% in the data. The remaining data moments are taken across the firm age grid, so I display the estimated parameter values in Table 2 and plot the model fit in Figure 3. Overall, the model achieves a good fit, with an objective function value of just under 12 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, wages paid by firms in the oldest age bin (11+ years old) are about 1.3 times higher than 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 matches average firm size by firm age almost exactly, with the exception of the oldest firm age bin. The estimated parameters of the vacancy cost level c_y imply that vacancy costs are increasing and convex in firm age.

[25]To conserve on notation, I suppress time subscripts.

Figure 3: Model Fit: Targeted Moments



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

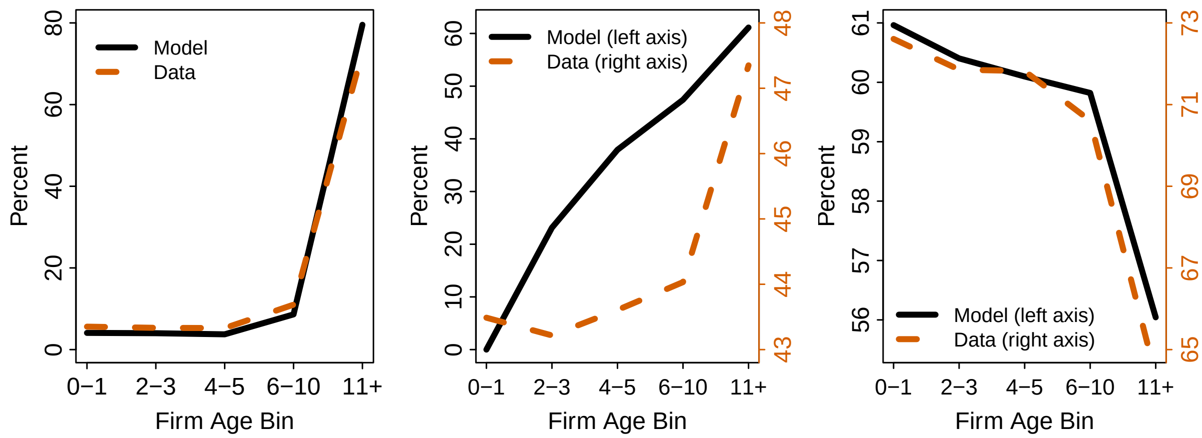
Hence, the oldest firms face the highest per-unit vacancy posting costs. The oldest firms in the model are also the largest, with an average size of about 25 employees (vs. about 18 in the data).

Dropping the aggregate job finding rate from the vector of target moments allows me 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 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 vs. data does not substantially affect my results and if anything could moderate them.

Non-Targeted Moments I now discuss the model fit to several moments that I do not explicitly target in my calibration exercise. Figure 4 and Figure 5 plot the model fit to moments related to the worker and firm life-cycles, respectively. Focusing first on the firm life-cycle, Figure 4 shows that the model captures other moments in the data that vary across the firm age distribution. In addition to closely matching average firm size by firm age, the model captures the employment distribution across firm age bin (panel 4a). As

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

(a) Employment Share (b) Poaching Share (c) Share of Workers Age < 45



Notes: In each panel, the black solid lines show the model moments and the red dashed lines show the corresponding moments in the data. Different vertical scales used for comparison. Data are from the Census Bureau's BDS, Job-to-Job Flows (J2J), and QWI databases, respectively. See Online Appendix F for details on moment construction.

discussed above, old firms are slightly larger and have a higher employment share than in the data. Next, 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 4b). Relative poaching shares in the model determine the direction of net job ladder moves; because old firms have the highest poaching shares, they sit at the top of the job ladder (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.[26] Lastly, 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 4c). Though the absolute magnitudes differ slightly, the relative profile across the life-cycle is close to that in the data.

The model generates this pattern through the following channel: young workers join the unemployment pool and begin searching for jobs (during the matching stage) when they enter the labor market at the beginning of their life-cycle; 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 share of younger workers at younger

[26] In the calibrated 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 this pattern in the data, but as long as the poaching share increases over the firm life-cycle on average, the main mechanism is preserved.

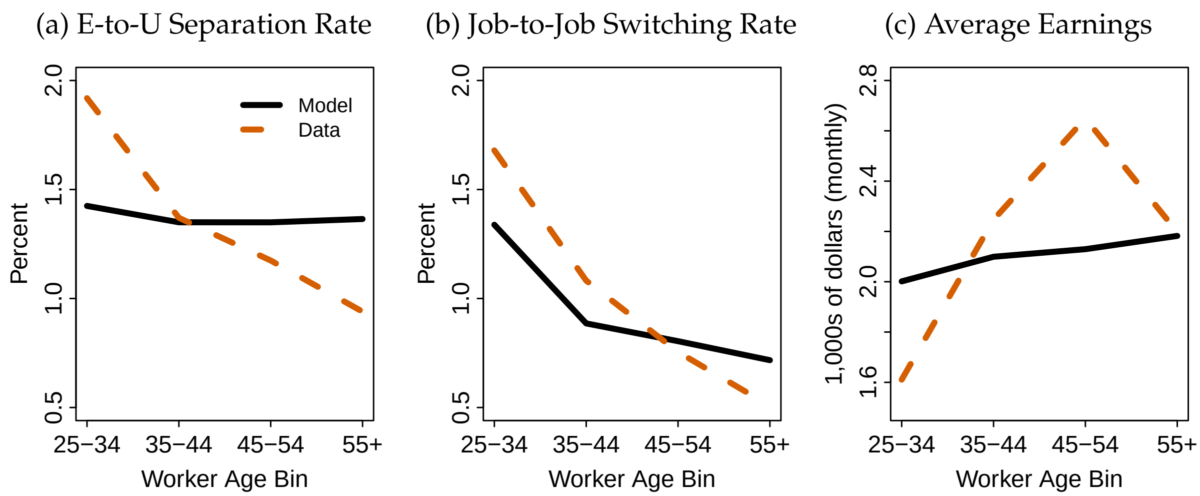
firms is larger. Therefore, capturing the poaching share across firm age determines the life-cycle sorting patterns of employment.

Figure 5 shows that although it cannot match moments related to the worker life-cycle in quantitative terms, the model does a decent job at capturing them qualitatively. First, panel 5a shows that the employment-to-unemployment separation rate declines over the life-cycle in both the model and the data. I calibrate separations δ_y to vary only by firm age, so the only force that generates differences in separations across the worker life-cycle is the degree to which young vs. old workers sort into different firms. Because younger workers sort into younger firms with higher separation rates, they have a higher chance of leaving their jobs than older workers. Next, panel 5b shows that the job-to-job switching rate declines over the worker life-cycle in both the model and the data. The model accounts for this pattern through the exogenously set search intensity parameters ϕ_x^e as well as the life-cycle sorting patterns: young workers occupy lower rungs of the job ladder, on average, and are therefore more likely to switch jobs if contacted by a firm. Lastly, panel 5c shows that wages increase, on average, over the worker life-cycle. The model accounts for this pattern through two channels, which both can be understood by inspecting the wage equation. The direct "productivity" component of the wage equation is higher for older workers because they are sorted into older, more productive firms, on average; the indirect "renegotiation benefit" component of the wage equation is higher (wages are lower) for younger workers because they are sorted into younger firms on lower rungs of the job ladder. The figure shows that through the lens of the model, this mechanism accounts for some of the increase in wages over the life-cycle.

Discussion Firms differ economically across the life-cycle along several dimensions, and the goal of the calibration is to capture those that are relevant for the job ladder mechanism at the heart of the model. First, young firms are more likely to shut down than older firms, on average. This is captured in the model 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 match output function p_y; I estimate this profile to be increasing in firm age, which could reflect either growth or selection effects (Hopenhayn, 1992). Lastly, young and old firms may face different costs associated with expanding their scope, which the model captures through the vacancy cost level by firm age c_y. I estimate that average vacancy posting costs are higher for older firms, indicating that it is easier for young firms to expand (Haltiwanger et al., 2013).

Several different underlying forces may give rise to firm dynamics of this nature.

Figure 5: Model Fit: Non-Targeted Moments, Worker Age



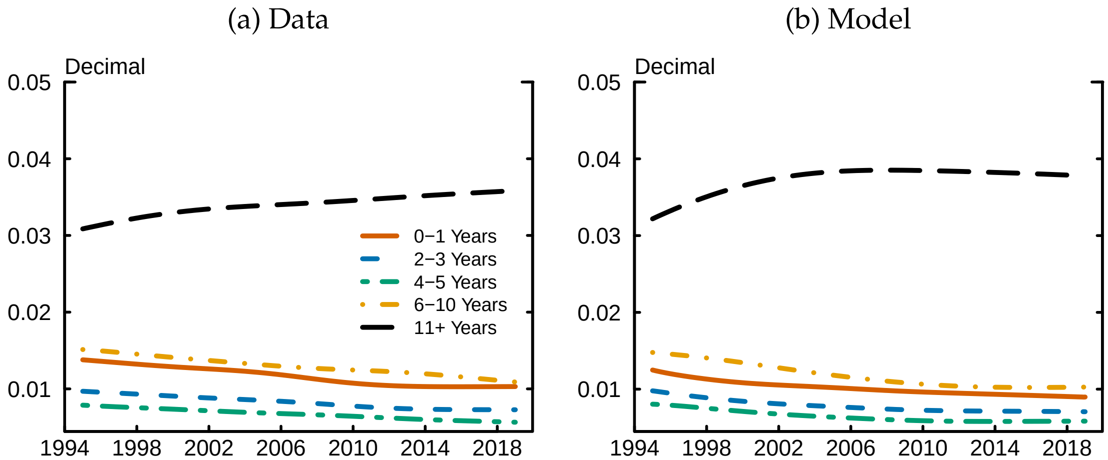
Notes: In each panel, the black solid lines show the model moments and the red dashed lines show the corresponding moments in the data. Data are from the Current Population Survey (CPS), J2J, and QWI, respectively. See Online Appendix F for details on moment construction.

However, rather than explicitly microfounding these mechanisms, the model and calibration strategy provide a reduced-form accounting of the firm life-cycle. As discussed above, I find that this also captures important features of the worker life-cycle, highlighting the relevance of the firm-life cycle for workers' job ladder dynamics. For instance, the job ladder mechanism at the heart of the model – old firms are ranked higher on the job ladder than young firms – accounts for the life-cycle sorting patterns of employment and also captures the life-cycle profile of worker transition rates and wages to a reasonable degree. The experiment in the next section follows a similar approach: take firm life-cycle dynamics as given and study their implications across worker age groups.

5 Quantifying the Effects of Declining Business Dynamism

Using the calibrated model, I now simulate a decline in business dynamism in order to quantify its impacts on workers at different stages of the life-cycle. Starting from the initial steady state firm distribution in 1994, I decrease the firm entry rate as in the data and study the effects on labor market outcomes. I also allow exit rates to evolve as in the data. I first describe the calibration of the time path of the entry and exit rates below. Then, I discuss the effects of declining dynamism on labor market outcomes in the aggregate and across cohorts of workers.

Figure 6: Mass of Firms by Firm Age $m_t(y)$



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. Sample includes only male workers age 25 and over. Series are HP-filtered using an annual smoothing parameter. See Online Appendix F for details on moment construction.

5.1 Calibrating the Law of Motion for the Mass of Firms

Equation 12 contains the law of motion for the mass of firms, which I reproduce here.

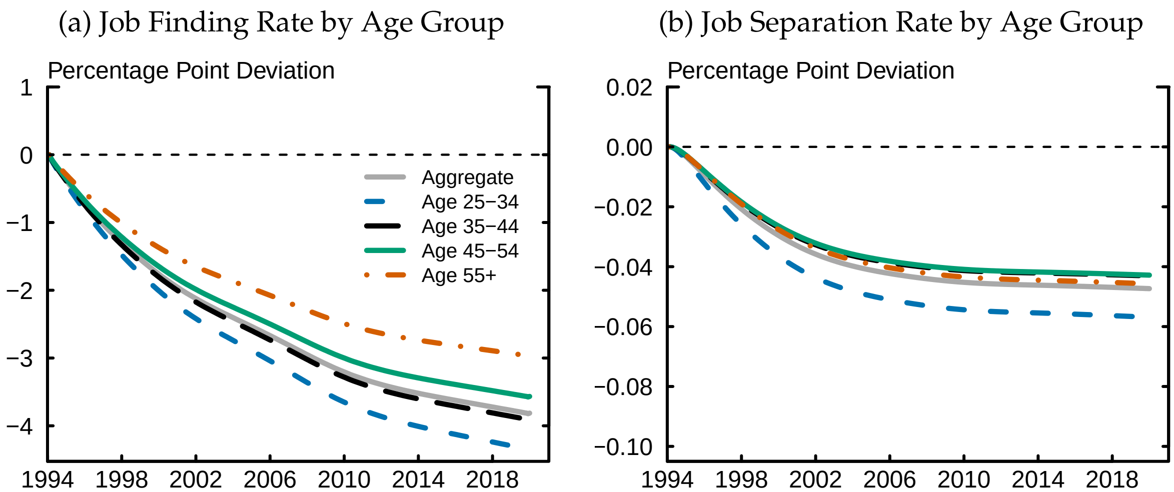
$$m_{t+1}(y') = \Pi_{y'|y} \cdot \big(1 - \zeta_{y,t}\big) m_t(y) + \gamma_t \cdot \mathbb{1}\{y' = \underline{y}\}$$

I calibrate the time path of the mass of firms by firm age bin so as to be as close to the data as possible. Then, I feed the resulting evolution of the mass of firms by firm age bin into the model and study the effects on labor market outcomes. This exercise takes *as given* the change in firm dynamics inherent in the law of motion for $m_t(y)$.

In the data, I observe: (i) exit rates by firm age bin and (ii) the ratio of the total number of firms in the economy to the total number of workers in the labor force.[27] To calibrate the law of motion for the mass of firms, I first take exit rates $\zeta_{y,t}$ directly from the data. I impute the entry rate γ_t to match the ratio of firms to the labor force $\mathcal{M}_t$ in the data. Figure 6 shows the resulting process for the mass of firms by firm age. I then feed this process into the model and study the response of the economy along the transition path.

[27] Online Appendix B plots these series. I HP-filter each series to abstract from business cycle fluctuations.

Figure 7: Effects on Labor Market Flows



5.2 Effects on the Labor Market

Figures 7 and 8 show the effects of the decline in business dynamism on key labor market variables. As the mass of firms in the economy declines, the total number of vacancies in the economy decreases. This effect can be seen by inspecting the formula for aggregate vacancies in a given time period V_t.

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

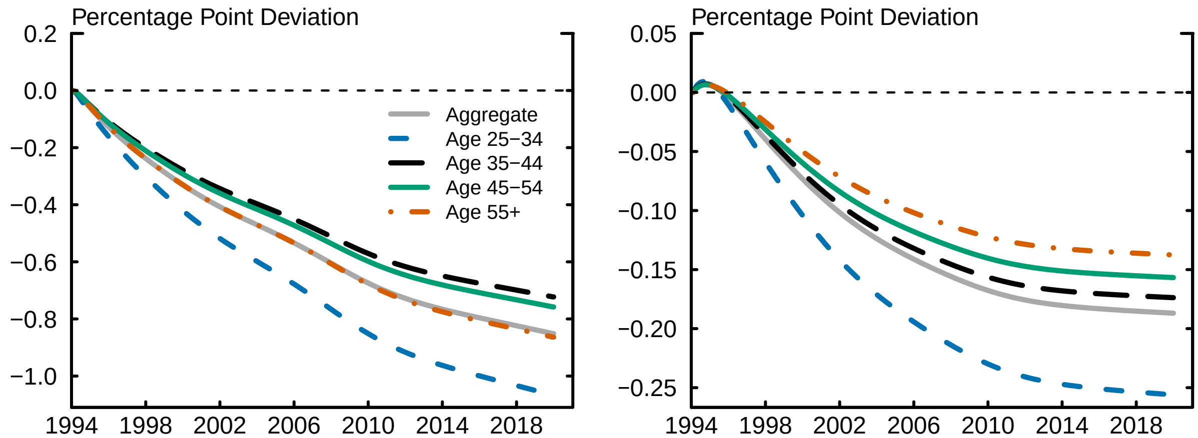
Aggregate vacancies are made up of two components. The first is the number of firm-level vacancies $n_t(y)$, which is pinned down by firms equating the costs and benefits of vacancy posting. Firm level vacancies are then scaled by the total number of firms in each age bin $m_t(y)$. Due to the decline in business dynamism, the mass of firms $m_t(y)$ declines for all firm ages, which directly decreases V_t. The amount that V_t declines along the transition path then depends on the degree to which firm-level vacancies $n_t(y)$ respond to the drop in dynamism. This is determined by the parameters of the vacancy cost function, the expected value of a filled vacancy $J_t(y)$, and the rate at which firms contact workers μ_t.

$$n_t(y) = \frac{\mu_t \cdot J_t(y)}{c_y}$$

Along the transition path, the expected value of a filled vacancy $J_t(y)$ increases because there are more unemployed workers searching for jobs. 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 (see Equation 4). In

Figure 8: Effects on Mobility and Employment

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



addition, the firm contact rate μ_t does not respond along the transition path and stays at a corner solution where a firm posting vacancies will certainly contact a worker. This corner solution arises from the matching function because the total mass of firms is much smaller than the total mass of workers in the calibrated model.[28] Therefore, the number of firm level vacancies $n_t(y)$ increases slightly along the transition path due to 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 declining dynamism on V_t.

The decline in V_t implies that the contact rate for workers λ_t, which is proportional to V_t, also 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 4 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 in the economy fall by about 0.04 percentage points, which results from a composition effect (panel 7b). As the share of young firms, which have high job destruction rates, declines, the share of workers matched with older firms, which have lower job destruction rates, increases. 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

[28]Total matches in the economy cannot be lower than the mass of searching workers or the mass of firm vacancies so that the matching function is $\Psi(L_t, V_t) = \min\{L_t, V_t, L_t^{\alpha} V_t^{1-\alpha}\}$.

Table 3: Quantifying the Effects of Declining Dynamism

Change: 1994–to–2019	Model	Data	Explained
Panel A: Employer Switching Rate			
Age 25–34	-0.26 pp	-0.37 pp	68.83%
Age 35–44	-0.17 pp	-0.20 pp	87.36%
Age 45–54	-0.16 pp	-0.10 pp	159.23%
Panel B: Employment–to–Population Ratio			
Age 25–34	-1.07 pp	-3.23 pp	33.04%
Age 35–44	-0.72 pp	-1.09 pp	66.53%
Age 45–54	-0.76 pp	-2.04 pp	37.09%

Notes: Model and Data columns show changes between 1994 and 2019. Units are monthly rates in percentage points (pp). Explained column displays 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 Annual Social and Economic Supplement (ASEC) of the Current Population Survey (CPS), following the methodology of Molloy et al. (2016). Employment–to–population ratio is from the Bureau of Labor Statistics (BLS) Labor Force Statistics (LFS) database. Sample includes only male workers. Series are HP-filtered using an annual smoothing parameter.

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 vs. 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.[29] 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 in terms of job switching are present for the youngest worker age group.

5.3 Contribution of Declining Dynamism to Declining Mobility

I now examine the degree to which the model's predictions capture the evolution of certain labor market series in the data during the period under consideration. Table 3 shows the contribution of declining dynamism to changes in labor market outcomes.

Between 1994 and 2019, males between the ages of 25–54 experienced a decline in rates of mobility as well as overall employment. In the data, the rate at which workers switch between jobs at different firms fell by about 0.5 percentage points on a monthly basis. However, this decline was not uniform for all worker age groups. In particular,

[29] This effect holds to a lesser extent for workers in the 55+ age bin who are nearing retirement, as total match surplus internalizes their higher exit rates.

employer switching fell by more for younger worker age groups, meaning that each successive cohort of labor market entrants has faced a lower rate of employment mobility. The counterpart in the model is the job-to-job flow rate, which measures the rate at which workers switch directly between jobs at different firms. As in the data, employer switching rates for younger workers in the model decline by more in response to the decline in the firm entry rate. Moreover, the model accounts for over 65% percent of the decline in employer switching across worker age groups.[30]

The model also accounts for the fact that average employment rates declined for workers under the age of 55 between 1994 and 2019. Table 3 shows that these workers experienced declines in their employment-to-population ratios over this time horizon. The model counterpart of these series is the non-employment rate, as the workers in these demographic groups are highly attached to the labor market and trends in the data are likely not driven by workers dropping out of the labor force for non-economic reasons. Through the lens of the model, declining business dynamism accounts for between 30 and 70 percent of the empirical trends in the employment rate across worker age group.

5.4 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). Figure 9 shows that although the decline in employer switching was larger for younger workers, the share of younger workers 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.

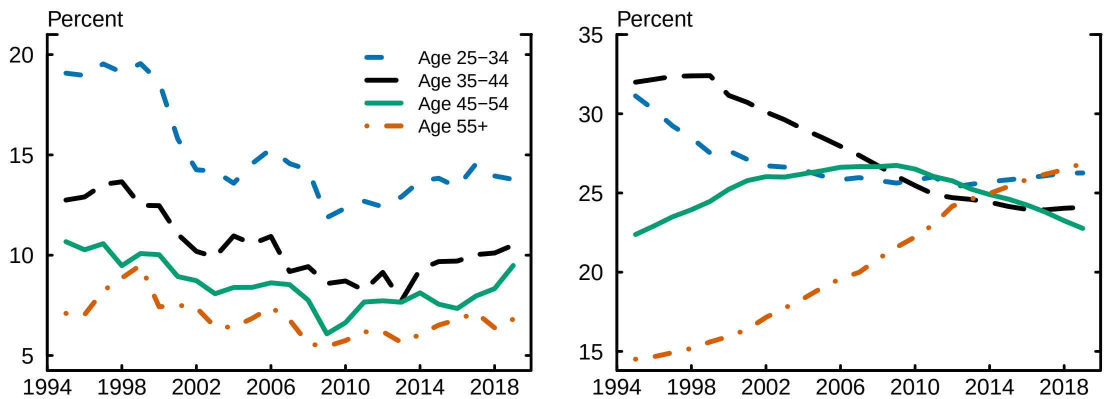
To assess whether the changing age composition of the U.S. labor force is responsible for the *aggregate* decline in job switching, I perform the following shift-share analysis. Let $EE_{a,t}$ denote the job switching rate and $\pi_{a,t}$ denote the labor force share of worker age group a.[31] I decompose changes in the aggregate job switching rate EE_t by holding either $EE_{a,t}$ or $\pi_{a,t}$ fixed at its 1994 value 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

[30]For the oldest worker age group, the business dynamism induced decline in employer switching is larger than the decline in employer switching in the data. See Table 3.

[31]I use the same age bins as in the model and data analysis sections. Results are robust to using employment shares instead of labor force shares.

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.

influence of demographic change, holding the life-cycle profile of the job switching rate constant; the "interaction" term captures the residual wherein 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.

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

	Data				Model			
	Total	*Within*	*Between*	*Interaction*	*Total*	*Within*	*Between*	*Interaction*
Change (p.p.)	-3.85	-3.21	-1.11	0.47	-3.78	-3.53	-1.39	1.16
Explained (%)	100	83.42	28.89	-12.31	100	93.43	36.89	-30.58

Notes: Data on employer switching rate and labor force share are from the CPS and LFS, respectively. Sample includes only male workers. Rates annualized in the model to be consistent with the data.

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 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 9). 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.[32]

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.

6 Welfare Implications of Declining Business Dynamism

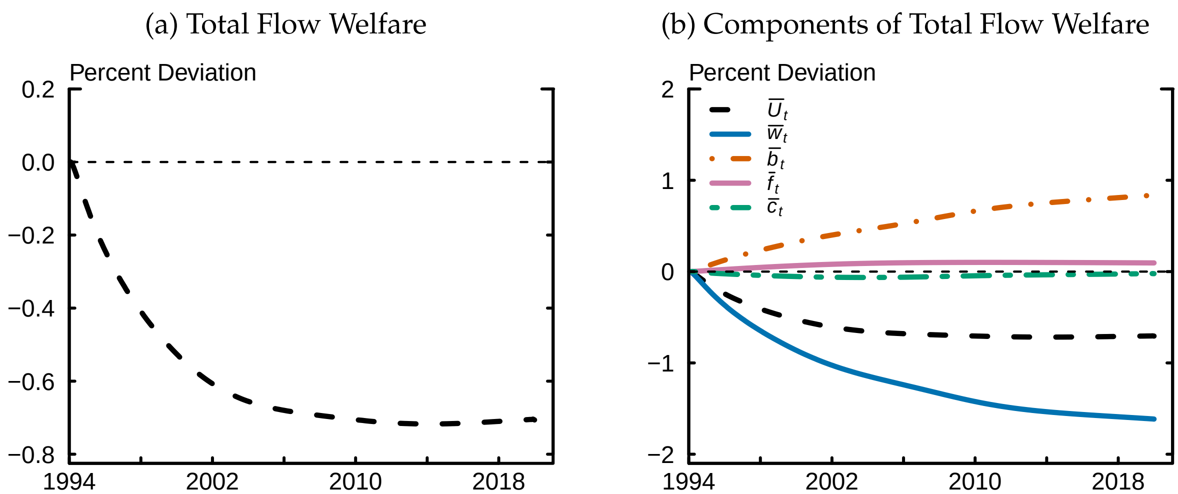
Lastly, I examine the consequences of the decline in business dynamism for total welfare in the economy and welfare for workers at different stages of their life-cycle. I return to the experiment wherein I hold worker labor force shares constant and allow the firm law of motion to evolve as in the data.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

6.1 Welfare Measures

The most natural measure of welfare in the model would be the value function for unemployed workers $W^u(x)$. However, this is exogenously pinned down by the sequential auctions protocol, so I instead use a flow value concept of welfare. Let $\bar{w}_t$ denote the flow welfare value of employed workers, $\bar{b}_t$ denote the flow welfare value of unemployed workers, $\bar{f}_t$ denote the flow welfare value of filled vacancies, and $\bar{c}_t$ denote the flow wel-

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

Figure 10: Flow Welfare Decomposition



fare value of unfilled vacancies at time t. These objects are defined as follows:

$$\bar{w}_t \equiv \int\int w_t(x,y)e_t(x,y)\,\mathrm{d}\,x\,\mathrm{d}\,y \qquad \bar{b}_t \equiv \int b\,u_t(x)\,\mathrm{d}\,x$$

$$\bar{f}_t \equiv \int (p_t(y) - w_t(y))m_t(y)\,\mathrm{d}\,y \qquad \bar{c}_t \equiv \int \tilde{c}_t(y)m_t(y)\,\mathrm{d}\,y$$

where $p_t(y) = \int p_y\, e(x,y)\,\mathrm{d}\,x$ represents total match output by firm age bin, $w_t(y) = \int w_t(x,y)\,e(x,y)\,\mathrm{d}\,x$ represents total wages by firm age bin, $\tilde{c}_t(y) = C_y\big(\pi_v^u(y)\,n_t(y)\big)$ represents flow vacancy posting costs by firm age y, and $\pi_v^u(y)$ is the share of unfilled vacancies by firm age bin. Total flow welfare in the economy at time t is given by $\bar{U}_t = \bar{w}_t + \bar{b}_t + \bar{f}_t - \bar{c}_t$.

6.2 Decomposing Total Flow Welfare

Using the definition of total flow welfare, we can decompose the percentage change in welfare in the economy into each of its components. Let $dX_t = X_t - X_0$ denote a deviation of the variable X_t from its steady state level X_0. Also, let $\Delta X_t = \frac{dX_t}{X_0}$ denote a percentage deviation of the variable X_t from its steady state level X_0. Changes in total flow welfare may be decomposed as follows.

$$\Delta\bar{U}_t = \frac{d\bar{w}_t}{\bar{U}_0} + \frac{d\bar{b}_t}{\bar{U}_0} + \frac{d\bar{f}_t}{\bar{U}_0} - \frac{d\bar{c}_t}{\bar{U}_0} \tag{13}$$

The results of this decomposition exercise are plotted in Figure 10. The components that have the largest contributions to the change in total flow welfare are employed workers welfare $\bar{w}_t$ and unemployed workers welfare $\bar{b}_t$. Along the transition path, these measures impact overall welfare in opposite directions. A decline in $\bar{w}_t$ has a negative effect on $\bar{U}_t$, while an increase in $\bar{b}_t$ has a positive effect on $\bar{U}_t$. The former effect dominates for the entirety of the transition path, so total flow welfare falls over this time horizon.

The changes in employed and unemployed worker welfare follow from the results presented in the previous section. As business dynamism falls, there is a large decline in employment and a corresponding increase in the unemployment rate for all age groups. Therefore, aggregating across a smaller (larger) number of employed (unemployed) workers results in lower (higher) overall welfare among these groups, notwithstanding changes in the flow payoffs that each group receives. For unemployed workers, these are constant along the transition path because b does not change over time (there are no changes in match-level output p_y). Hence, the effects on $\bar{b}_t$ are straightforward to understand: a larger number of unemployed workers receiving the same flow benefit b results in overall larger $\bar{b}_t$. For employed workers, wages $w_t(x, y)$ also change along the transition path, so the effects driving the change in $\bar{w}_t$ are not as clear. I further decompose the different margins that affect $\bar{w}_t$ below.

6.3 Decomposing Employed Worker Flow Welfare

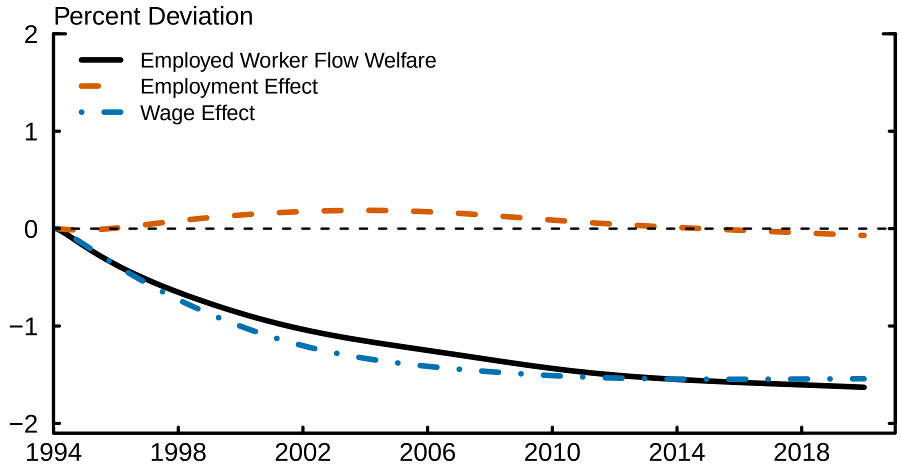
I now decompose changes in employed workers' welfare $\bar{w}_t$ into two margins. The first margin stems from changes in employment rates, while the second margin stems from changes in workers' wages. Let $e_0(x, y)$ denote match-level employment in steady state and let $w_0(x, y)$ denote match-level 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:

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

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 $\bar{w}_t$ 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 $\bar{w}_t$ changes due to changes in match-level wages, holding employment by worker age and firm age constant at their steady state values.

Figure 11 plots this decomposition. It is clear from the figure that the $Wage\ Effect$

Figure 11: Employed Worker Flow Welfare Decomposition



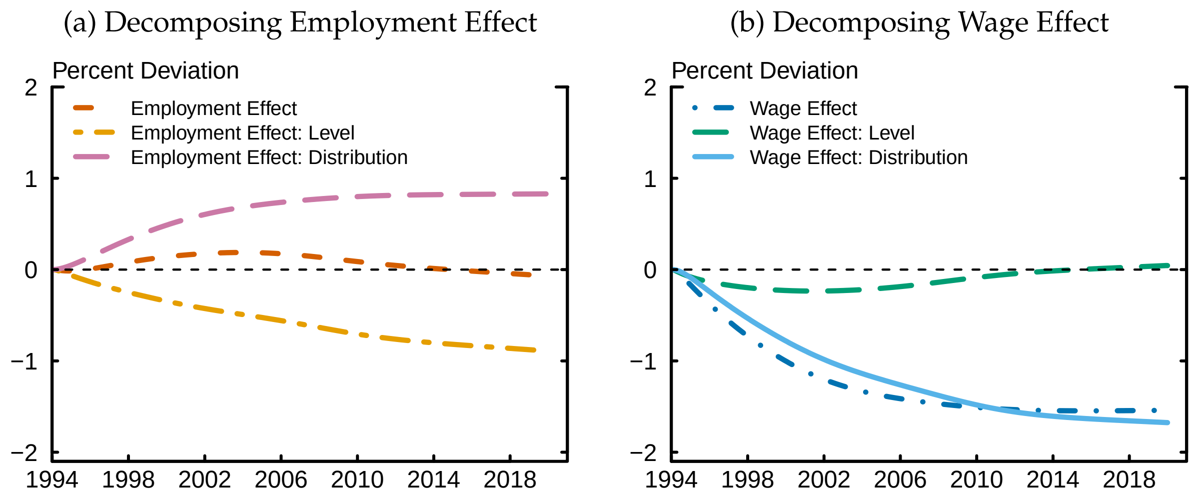
dominates, driving the overall decline in employed worker flow welfare. Along the transition path, employed workers receive lower wages, driven by lower between-firm poaching competition. Although the employment probability declines in response to the decline in business dynamism, the $Employment\ Effect$ plays only a small role in the decline in employed workers flow welfare.

However, examining the changes in these component masks important sorting dynamics along the transition path. To further inspect these sorting patterns, I provide an additional decomposition of the $Employment\ Effect$ and the $Wage\ Effect$ into components stemming from changes in their levels and distributions. For instance, the level effect shows the degree to which changes in the level of employment or wages affect employed worker flow welfare. The distribution effect shows how changes in the ages of matches workers sort into affects employed worker flow welfare.

Figure 12 plots this decomposition. First, we can see that the $Employment\ Effect$ is driven by offsetting changes in the level and distribution (panel 12a). 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 towards older firms that are more productive and pay higher wages.

Similar dynamics shape the evolution of the $Wage\ Effect$ (panel 12b). 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

Figure 12: Level Effect vs. Distribution Effect



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 towards 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.

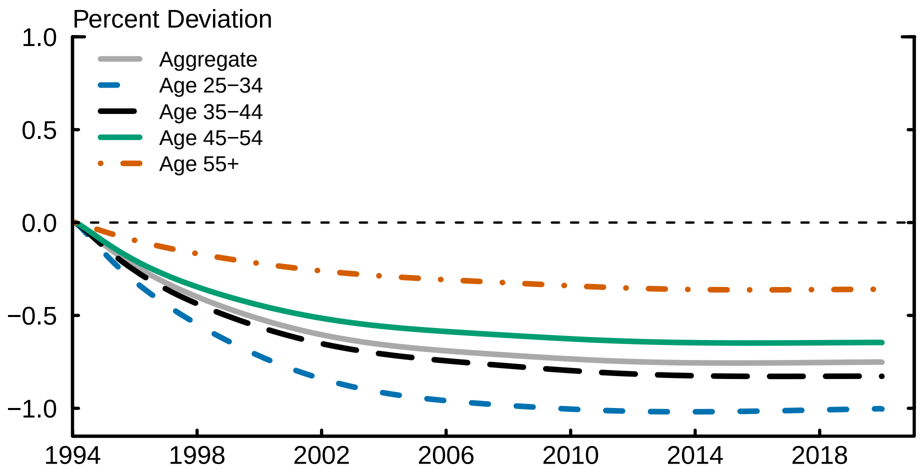
6.4 Welfare Changes by Worker Cohort

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 13 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 0.7 percent along the transition path, while the youngest age group of workers (25–34) experiences as much as a 1 percent decline in welfare. Though it recovers slightly by the end of the period under consideration, this is driven by an increase in nonemployment among young workers and therefore a larger increase in $\bar{b}_t$ for this group.

The larger decline in flow welfare for younger workers is driven by the fact that they

Figure 13: Worker Flow Welfare by Age Group



experience 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 total worker flow welfare for younger cohorts.

7 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 towards 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 towards 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.

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