Workers' Job Prospects and Young Firm Dynamics*

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Abstract

This paper investigates how worker beliefs and job prospects shape wages and growth at young firms and aggregate outcomes. Building a heterogeneous-firm directed search model in which workers gradually learn about firm fundamentals, I show that learning under labor market frictions generates endogenous wage differentials and distinct labor market outcomes for young firms. In particular, high-performing young firms pay higher wages than observationally equivalent mature firms, while low-performing young firms offer lower wages than their mature counterparts. These wage differentials create hiring and retention frictions for high-performing young firms. Reductions in either information frictions or search frictions compress wage differentials, strengthen selection by enhancing the growth of high-potential young firms, and increase aggregate productivity. The model's predictions are supported by U.S. administrative employer–employee matched data.

JEL: E24, J31, J41, L25, L26, M13

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1 Introduction

Firms' ability to attract workers is central to job creation and employment growth. Yet, in practice, firms—especially small and young ones—often struggle to find employees, with vacancies

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taking time to fill.[1] In frictional labor markets, firm growth depends critically on worker participation and incentives, which shape firms' ability to hire, retain, and scale their workforce. When choosing jobs, workers evaluate firms based on expected wages, separation risk, and future career prospects—what I refer to as job prospects—which depend on beliefs about firm fundamentals. These considerations become more pronounced in the presence of search frictions and are especially salient for young firms. Young firms have limited histories, and their performance is a noisy signal of underlying fundamentals. This nascency generates uncertainty that shapes workers' job prospects differently and can constrain the hiring and retention of high-potential young firms early in their lifecycle.

This channel has important aggregate implications. Young firms are a key driver of job creation, economic dynamism, and productivity growth. In the U.S., firms aged five years or less account for nearly 30% of job creation despite representing a small share of employment, with high-growth young firms alone contributing 21.22% of total job creation.[2] Young firms also account for a substantial share of productivity growth and exhibit higher worker turnover (Haltiwanger et al., 2012, 2013; Decker et al., 2014, 2016; Foster et al., 2018), playing a key role in resource allocation and allocative efficiency. If worker beliefs and labor market frictions hamper growth of high-potential young firms, the consequences extend beyond individual firms and adversely impact the aggregate economy. Yet little is known about how workers' job prospects, interacting with labor market frictions, shape firm dynamics and aggregate outcomes.

This paper addresses this gap, both theoretically and empirically, by studying how workers' job prospects and beliefs about firms determine wages and growth of young firms and quantifying the aggregate implications of this channel. I develop a heterogeneous-firm directed search model with learning about firm types to characterize the underlying mechanism. Empirically, I test the model with two comprehensive databases from the U.S. Census Bureau; the Longitudinal Business

[1] In the 2024 Small Business Credit Survey conducted by the U.S. Federal Reserve Banks, 51% of firms cited difficulties in hiring and retaining workers. The challenge was even more pronounced among growing firms, 61% of which reported such constraints. A survey by the National Federation of Independent Business (NFIB) found that 36% of small, young business owners reported having job openings that they could not fill. Also, based on a survey by SCORE, 52% of startups cited difficulty filling job openings, and amongst startups that reported unfilled job openings, 75.7% reported they could not find qualified applicants. In a Danish survey conducted by Bertheau et al. (2023), younger and smaller firms are particularly subject to search and training frictions.

[2] This is based on the Business Dynamics Statistics, 1998–2014. High-growth firms are defined as those with DHS employment growth above 0.8, i.e., $\frac{(Emp_{it}-Emp_{it-1})}{0.5(Emp_{it}+Emp_{it-1})} > 0.8$, representing 3.36% of employment.

Database (LBD) and the Longitudinal Employer-Household Dynamics (LEHD).

First, I document stylized facts on pay differentials between young and mature firms using employer–employee administrative data from the U.S. Census Bureuau. I find that young firms pay lower wages unconditionally, but conditional on worker heterogeneity and observable firm characteristics (e.g., size and productivity), they pay higher earnings on average than otherwise similar mature firms. These patterns cannot be rationalized by standard firm dynamics models or labor search frameworks without age-specific components.[3]

To account for the empirical patterns, I develop a directed search model with learning about firm fundamentals, extending Schaal (2017) by incorporating firm-type learning in the spirit of Jovanovic (1982). In the model, workers learn about firm fundamentals in the presence of labor market frictions. This creates a key feature that workers update beliefs about firm productivity type over the firm life cycle and make decisions to join or stay at a firm based on these beliefs. The interaction between learning and search frictions endogenously generates wage differentials between young and mature firms, even among firms with identical observable characteristics.

Specifically, I show that young firms with high demonstrated potential—defined by high past-average performance—must offer wage premia to attract workers relative to otherwise similar mature firms. This is due to the relative lack of records for young firms, so that workers are not fully convinced by their average performance. Conversely, young firms with low demonstrated potential can offer wage discounts relative to mature counterparts, as their short histories leave room for upside risk in workers' beliefs. This asymmetric impact of limited histories is a novel prediction of the model and provides a microfoundation for the observed average earnings premia of young firms relative to similarly performing mature firms in the pooled data. As a consequence, wage differentials translate into hiring and retention frictions for high-performing young firms: they exhibit lower hiring rates and higher worker outflows—through quits driven by poaching and layoffs—relative to otherwise similar mature firms.

The model quantifies how learning interacts with labor market frictions and characterizes aggregate firm dynamics and productivity. Reductions in either information frictions or search frictions increase entry and young-firm activity. The employment share of high-performing young

[3]Most existing works consider firm heterogeneity in size or productivity but do not explicitly account for the distinction of firm age, which cannot distinguish young and old firms controlling for size and productivity.

firms rises by 5.2 percentage points without information frictions and by 22.4 percentage points without search frictions. In both counterfactuals, the firm-level productivity distribution shifts rightward, reflecting the expansion of high-productivity firms. Intuitively, eliminating uncertainty narrows gaps in workers' job prospects between young and mature firms, while removing search frictions alleviates workers' concerns about future prospects at a firm with greater labor mobility. When either friction is removed, wage differentials disappear, strengthening selection: high-performing young firms expand more rapidly, while low-performing firms contract and exit. This reallocation of employment toward more productive firms raises aggregate productivity.

I then return to the data to test the model's predictions. After controlling for worker heterogeneity and observable firm characteristics, I find that high-performing young firms pay wage premia relative to observationally similar mature firms, while low-performing young firms pay wage discounts. These earnings differentials are also negatively associated with firm hiring and employment growth. This is consistent the model's prediction that learning in frictional labor markets affects worker participation, creating wage differentials and impacting firm growth.

To assess the role of learning, I exploit industry-level variation in the noise-to-signal ratio, constructed from the dispersion of firm-level productivity shocks and fixed effects. Earnings differentials are more pronounced in high-uncertainty industries and attenuated in low-uncertainty ones. Finally, lower uncertainty and greater job mobility—indicative of weaker labor market frictions—are associated with higher firm entry, stronger young-firm activity, particularly among high-performing young firms, and higher productivity at the industry level, supporting the model's aggregate implications.

This paper contributes to studies on firm dynamics and the growth of young firms. Much previous research emphasizes the importance of financing constraints for entrepreneurship (Holtz-Eakin et al., 1994; Cooley and Quadrini, 2001). Other studies including Foster et al. (2016), Decker et al. (2020), and Akcigit and Ates (2023) emphasize frictions related to customer base accumulation, adjustment costs, or knowledge spillovers as barriers to firm entry and the growth of young firms. Sterk et al. (2021) highlight the role of ex-ante firm heterogeneity for the growth of high-growth young firms. This paper expands this literature by linking firm dynamics to labor market frictions and highlighting worker participation margin based on their job prospects as a novel source affecting firm entry and young firm growth.

This mechanism is closely connected to understanding recent trends or heterogeneity in firm dynamics and labor market fluidity. A large body of work documents the slowdown of U.S. dynamism, reflected in declining job reallocation, reduced worker mobility, and slower firm entry and growth (Davis and Haltiwanger, 2014; Decker et al., 2014, 2016). Decker et al. (2020) attribute the decline in job reallocation, firm entry, and exit to the weakening responsiveness of firms to idiosyncratic productivity shocks, potentially due to rising adjustment costs or distortions correlated with fundamentals. My paper adds to this literature by providing a workhorse framework that highlights how increased labor market frictions and shifting worker incentives can account for these trends. Moreover, varying degrees of labor market frictions and worker incentives can help us understand heterogeneous patterns of firm dynamics across different environments, such as across countries (Biondi et al., 2023).

In addition, this paper is also relevant to a large set of literature studying inter-firm wage differentials (Abowd et al., 1999; Card et al., 2013; Bloom et al., 2018; Card et al., 2018; Lopes de Melo, 2018; Song et al., 2019). Some studies mainly focus on wage differentials by firm age (Brown and Medoff, 2003; Burton et al., 2018; Kim, 2018; Babina et al., 2019; Sorenson et al., 2021). However, the findings exhibit disparate results across various specifications and abstract from a comprehensive theory providing a robust mechanism to explain them. This paper contributes to this literature by providing a rich structural model that guides a concrete mechanism generating earnings differentials of young firms. Guided by the model, the paper develops and estimates an empirical specification that isolates the part of inter-firm earnings differentials attributed to learning about firm fundamentals, as well as provides new datafacts supporting this channel: earnings premia (discounts) paid by high (low)-performing young firms relative to their equally-performing mature counterparts, along with the negative relationship between these pay gaps and firm performance.

Moreover, this paper is grounded in the directed labor search literature (Menzio and Shi, 2010, 2011) and related to firm dynamics model with search frictions (Elsby and Michaels, 2013; Kaas and Kircher, 2015; Coles and Mortensen, 2016; Schaal, 2017; Bilal et al., 2022; Elsby and Gottfries, 2022; Gouin-Bonenfant, 2022). This paper contributes to the literature by introducing firm lifecycle into a directed search framework through a firm-type learning process, along with endogenous firm entry, exit, and on-the-job search. This enables the distinction between young and old firms after controlling for observable characteristics and generates endogenous wage differentials between young firms and observably identical mature firms, as seen in the data. Furthermore, the model retains block recursivity, ensuring tractability without sacrificing richness. This feature allows for quantifying the aggregate implications of learning and labor market frictions and the resulting wage differentials for young firms in a tractable manner.

Lastly, this paper relates to the large literature on learning in labor markets. Most existing work studies employer learning about worker quality (Farber and Gibbons, 1996; Altonji and Pierret, 2001; Lange, 2007; Kahn and Lange, 2014; Carranza et al., 2022; Pastorino, 2024) or workers' learning about their own skills or job match quality (Papageorgiou, 2014; Baley et al., 2022). In contrast, this paper shifts the focus to firms by studying workers' learning about firm types and its implications for worker participation, wages, and firm outcomes. This mechanism introduces a novel channel through which workers' learning shapes firm dynamics and aggregate productivity.

The paper is structured as follows: Section 2 documents stylized facts of earnings paid by young firms; Section 3 develops a heterogeneous firm directed search model with a firm-type learning process and lays out the model's main analytical results; Section Section 4 describes the model calibration and quantitative analysis; Section 5 tests the model's implications using the data; and Section 6 concludes.

2 Descriptive Facts

2.1 Data

I construct a comprehensive employer–employee matched dataset by linking the Longitudinal Business Database (LBD) and the Longitudinal Employer–Household Dynamics (LEHD) data at the U.S. Census Bureau from 1998 to 2014. The LBD tracks the universe of U.S. establishments and firms annually beginning in 1976, while the LEHD contains quarterly employment and demographic information for workers drawn from the Unemployment Insurance (UI) system. The linked dataset covers approximately 60% of U.S. private-sector employment across 29 states.[4]

In LBD, I define firm age as the age of the oldest establishment that the firm owns when the firm is first observed in the data, following Haltiwanger et al. (2013). I label firms aged five years

[4]The 29 states are AL, AZ, CA, CO, CT, DE, ID, IN, KS, MD, ME, ND, NE, NJ, NM, NV, NY, OH, OK, OR, PA, SD, TN, TX, UT, VA, WA, WI, and WY.

or below as young firms. Firm size is measured as total employment. Firm-level productivity is measured as the log of real revenue per worker (normalized to 2009 U.S. dollars).[5] In LEHD, I focus on full-quarter main jobs that give the highest earnings in a given quarter and are present for the quarter prior to and the quarter after the focal quarter. This is due to the limitation of LEHD not reporting the start and end dates of a job.[6] I link the LEHD to the LBD and identify employers associated with each job held by workers. Further data details are provided in Online Appendix D.

2.2 Stylized Facts on Wage Differentials by Firm Age

Using this dataset, I document stylized facts on earnings paid by young firms. As a baseline specification, I estimate the following regression:

$$y_{it} = \beta Young_{j(i,t)t} + Z_{j(i,t)t}\gamma + \eta_t + \epsilon_{it}, \tag{1}$$

where y_{it} denotes the log of real Q1 earnings of worker i in year t, $j(i,t)$ indexes the employer of worker i in year t, $Young_{j(i,t)t}$ is an indicator for whether the employer is aged five years or less, $Z_{j(i,t)t}$ is a vector of firm-level controls—including log employment and log real revenue productivity—and η_t denotes year fixed effects.

Table 1 shows that young firms, on average, pay lower earnings than older firms. This result is robust to controlling for firm-level characteristics, although the magnitude of the earnings differential is attenuated. In the unconditional specification, young firms pay 11.8% lower earnings than older firms (column 1). Controlling for firm size and productivity reduces the differential to 8.5% (column 2).

Because industry composition differs systematically between young and old firms, I replace the year fixed effects η_t in regression (1) with industry–year fixed effects η_{gt}.[7] The qualitative results

[5] I use labor productivity to maximize the sample size as variables related to other input types are available only for a subset of manufacturing sector. In the U.S., within-industry correlation between labor productivity and real value added per worker is 0.82 (Bartelsman et al., 2013), and my analysis focuses on within-industry effects.

[6] For any worker-quarter pairs that are associated with multiple jobs paying the same earnings, I pick the job that shows up the most frequently in the worker's job history. This leaves one main job observation for each worker-quarter pair.

[7] There is substantial heterogeneity across sectors in the share of young firms. Using the Business Dynamics Statistics (BDS), I find that young firms are disproportionately represented in services, information, and retail trade, and underrepresented in manufacturing, wholesale trade, and the public sector. Decker et al. (2016) document similar patterns.

Table 1: Wage Differentials for Young Firms

	Earnings	Earnings	Earnings	Earnings
Young	-0.118***	-0.085***	-0.048***	-0.012***
	(0.004)	(0.003)	(0.002)	(0.002)
Firm Size		0.047***		0.085***
		(0.003)		(0.002)
Firm Productivity		0.398***		0.342***
		(0.006)		(0.004)
Observations	50,170,000	50,170,000	50,170,000	50,170,000
Fixed effects	t	t	gt	gt

Notes: The table reports estimates from the baseline earnings regression (1). The dependent variable is log real Q1 earnings. Firm size (log employment) and revenue productivity are included as controls in the second and fourth columns. The first two columns include year fixed effects, while the last two columns include industry–year fixed effects. Observation counts are rounded to the nearest 10,000 to mitigate disclosure risk. Estimates for the constant and fixed effects are suppressed. Observations are unweighted. Standard errors are robust. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

remain unchanged, but the estimated earnings gaps are substantially attenuated. The unconditional earnings gap declines from 11.8% to 4.8% (column 3), and the gap conditional on firm size and productivity declines from 8.5% to 1.2% (column 4). This attenuation indicates that a sizable share of the earnings differential reflects differences in industry composition rather than within-industry pay differences.

Furthermore, the literature shows that young firms disproportionately employ younger, less experienced, and lower-skilled workers on average (Ouimet and Zarutskie, 2014; Sorenson et al., 2021). To account for the effect of worker heterogeneity in earnings, I proceed as follows:

$$y_{it} = \delta_i + \eta_t + X_{it}\gamma + \epsilon_{it}, \tag{2}$$

where y_{it} is the log of Q1 earnings of worker i in year t, δ_i denotes worker fixed effects, η_t denotes year fixed effects, and X_{it} is a vector of time-varying worker controls, including quadratic and cubic polynomials in age centered at age 40.[8,9]

[8]Including worker fixed effects absorbs unobserved worker heterogeneity and sorting across firms. In robustness checks, I additionally control for worker skill using highest educational attainment. Firm fixed effects are retained in subsequent specifications as proxies for unobserved firm fundamentals that may contribute to young-firm earnings differentials. This specification allows me to focus on cross-sectional earnings differences across firm ages.

[9]I implement the iterative algorithm of Guimaraes and Portugal (2010), which helps to estimate a regression model with high-dimensional fixed effects without explicitly using dummy variables to account for the fixed effects.

Next, using residualized earnings, I estimate the following regression:

$$\hat{\epsilon}_{it} = \beta Young_{j(i,t)t} + Z_{j(i,t)t}\gamma + \mu_{g(j(i,t))} + \epsilon_{it}, \tag{3}$$

where $\mu_{g(j(i,t))}$ denotes industry fixed effects. Table 2 shows that, after accounting for worker characteristics, young firms pay 0.6% lower earnings to observationally equivalent workers (column 1). Once firm size and productivity are additionally controlled for, the sign of the differential reverses: young firms pay 0.8% higher earnings to the same type of worker relative to similarly performing older firms (column 2). These results are robust to the inclusion of state fixed effects $\delta_{s(j(i,t))}$ (columns 3 and 4). As another robustness check, I control for workers' prior employment status, $Z_{j(i,t-1)}$, using the AKM firm fixed effect associated with the worker's previous employer, along with a non-employment indicator.[10,11] This renders the unconditional earnings differential statistically insignificant (columns 5), while the earnings premium after controlling for firm size and productivity remains robust (column 6).

This suggests that much of the earnings differential associated with young firms is driven by industry composition and worker sorting, and is partially attributable to firm heterogeneity (e.g., size or productivity). In particular, young firms pay lower wages than mature firms in general, unconditional on worker types. However, when using residualized earnings—which account for worker heterogeneity across young and mature firms—and controlling for industry composition and firm characteristics, young firms in fact pay more than otherwise similar mature counterparts.

The existence of earnings differentials across firms is difficult to reconcile with a standard frictionless model. Moreover, canonical search models with firm heterogeneity (Elsby and Michaels, 2013; Kaas and Kircher, 2015; Schaal, 2017) cannot account for these patterns, as they do not generate wage dispersion across firms conditional on firm observable characteristics such as size and productivity. These findings therefore point to the presence of labor market frictions and the need for an additional dimension of firm heterogeneity that evolves over the firm life cycle. One

[10]This controls for potential ex post worker heterogeneity along the job ladder, which may affect workers' outside options, bargaining positions or contract values and, in turn, the level of earnings paid.

[11]For those workers previously employed before period t, their previous job is identified as the most recent full-quarter main job within the three most recent quarters before t. Next, I estimate the fixed effect for the previous employer (at the SEIN level) following Abowd et al. (1999). For workers who are not employed in any states in the previous period, I assign a non-employment dummy to them. More details are available in Online Appendix D. As a robustness check, I use earnings paid by the previous employer.

Table 2: Wage Differentials for Young Firms

	Earnings Residuals	Earnings Residuals	Earnings Residuals	Earnings Residuals	Earnings Residuals	Earnings Residuals
Young	-0.006***	0.008***	-0.006***	0.007***	0.001	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Firm Size		0.040***		0.040***		0.017***
		(0.001)		(0.001)		(0.000)
Firm Productivity		0.077***		0.076***		0.028***
		(0.001)		(0.001)		(0.001)
Observations	50,170,000	50,170,000	50,170,000	50,170,000	50,170,000	50,170,000
Fixed effects	g	g	g, s	g, s	g, s	g, s

Notes: The table reports estimates from the earnings residual regression (3). The dependent variable is the earnings residuals estimated in (2), taking out the effect of worker heterogeneity from the Q1 main job real earnings. The first two columns only take out industry fixed effect and the remaining columns additionally take out state fixed effect. The second and fourth columns control for firm size (log employment) and revenue productivity, while the last two columns additionally control for workers' prior employment status by using the AKM firm fixed effect associated with the worker's previous employer along with a non-employment indicator. Observation counts are rounded to the nearest 10,000 to avoid potential disclosure risks. Estimates for constant and industry fixed effects are suppressed. Observations are unweighted. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

plausible mechanism is the nascency of young firms: even when they exhibit observable performance comparable to that of mature firms, workers must learn about them and may form different perceptions of job prospects and incentives to join. As a result, in a frictional labor market, young firms may offer different wages than mature firms despite similar observable characteristics.

3 Theoretical Model

To account for the empirical patterns through the proposed learning mechanism and to derive implications for firm dynamics and aggregate outcomes, I develop a model of frictional labor markets with ex-ante firm heterogeneity. I extend Schaal (2017) by introducing a firm-type learning process à la Jovanovic (1982). The economy consists of heterogeneous firms and homogeneous workers with symmetric information. Both firms and workers are risk neutral and discount the future at rate β. Firms produce a homogeneous good.

3.1 Firm-type Learning Process

Firms (j) are born with time-invariant productivity types $\nu_j \sim N(\bar{\nu}_0, \sigma_0^2)$ that are normally distributed. Observed productivity P_{jt} for firm j at time t follows a log-normal process $P_{jt} = e^{\nu_j + \varepsilon_{jt}}$, where $\varepsilon_{jt} \sim N(0, \sigma_\varepsilon^2)$ is an i.i.d. shock across firms and time. Firms and workers do not see the types but only know the realized P_{jt} and the distributions of type ν_j and shocks ε_{jt}.[12]

Both entrants and workers start with a common prior $\nu_j \sim N(\bar{\nu}_0, \sigma_0^2)$ at firm birth. After observing P_{jt}, they update their beliefs using Bayes' rule. The posterior distribution satisfies $\nu_j|_{P_{jt}} \sim N(\bar{\nu}_{jt}, \sigma_{jt}^2)$, where the posterior mean $\bar{\nu}_{jt}$ and variance σ_{jt}^2 at the end of period t (or at the beginning of period $t+1$) evolve as

$$\bar{\nu}_{jt} = \frac{\left(\frac{\bar{\nu}_0}{\sigma_0^2} + \frac{\sum_{i=0}^{a_{jt}} \ln P_{jt-i}}{\sigma_\varepsilon^2}\right)}{\left(\frac{1}{\sigma_0^2} + \frac{a_{jt+1}}{\sigma_\varepsilon^2}\right)} = \frac{\left(\frac{\bar{\nu}_0}{\sigma_0^2} + \frac{a_{jt+1}\tilde{P}_{jt}}{\sigma_\varepsilon^2}\right)}{\left(\frac{1}{\sigma_0^2} + \frac{a_{jt+1}}{\sigma_\varepsilon^2}\right)}, \; \sigma_{jt}^2 = \frac{1}{\left(\frac{1}{\sigma_0^2} + \frac{a_{jt+1}}{\sigma_\varepsilon^2}\right)}, \tag{4}$$

where a_{jt} denotes firm age at period t, and $\tilde{P}_{jt} \equiv \frac{\left(\sum_{i=0}^{a_{jt}} \ln P_{jt-i}\right)}{a_{jt+1}}$ is the average log productivity observed up to period t (after observing P_{jt}). Henceforth, I refer to this as the past-average log productivity. Note that firm age and the past-average log productivity $(a_{jt+1}, \tilde{P}_{jt})$ are sufficient statistics for the posterior about firm type at $t+1$, which one can use to track job prospects for each firm.[13] Figure 1 illustrates the posterior beliefs across different firm ages, for a given level of past-average productivity.[14]

3.2 Labor Market and Contracts

Labor Market. The labor market is frictional. Search is directed on both the worker and firm sides. Firms post vacancies by paying a vacancy cost c and announce contracts to hire and retain workers each period. The labor market is a continuum of submarkets indexed by the utility

[12] The dispersion of firm-level types, σ_0, indicates the signal level, while the dispersion of shocks, σ_ε, reflects the noise level in the economy. In literature, the degree of uncertainty is often measured by the noise-to-signal ratio ($\frac{\sigma_\varepsilon}{\sigma_0}$).

[13] See Online Appendix A for more details and properties of the Bayes' rule.

[14] Note that in Bayesian learning, both firms and workers learn from observable performance to infer firms' fundamental types. Therefore, a firm's past-average productivity $\tilde{P}_{jt-1}$ indicates their "potential" type at the beginning of each period t, which converges to the firm's time-invariant type ν_j in the long run.

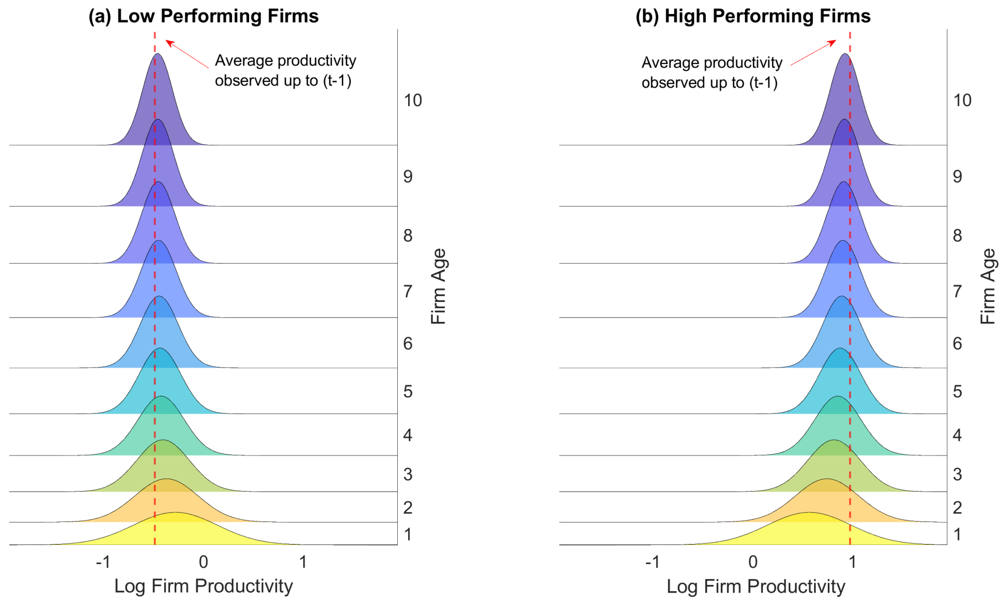

Figure 1: Posterior Distribution of Firm Type

value x_{jt} that firms (j) promise to workers in contracts.[15] Firms and workers choose a submarket to search in by considering a trade-off between the promised utility of a given contract and the corresponding matching probability. For each labor submarket x, I assume a CES matching function, $M(S(x), V(x)) = (S(x)^{-\gamma} + V(x)^{-\gamma})^{-\frac{1}{\gamma}}$, where $S(x)$ and $V(x)$ are the total number of searchers and vacancies, respectively. There is on-the-job search with search efficiency λ for employed workers.

Contracts. Contracts are written every period after matching occurs and before production takes place. Contracts are recursive, state-contingent and fully committed for firms. However, contracts are not committed for workers, allowing them to leave the firm at any time.[16] A contract $\mathbf{\Omega^i_{jt}}$ for worker i at firm j at t specifies the current wage w^i_{jt}, the next period utility $\tilde{W}^i_{jt+1}$, firm exit probability d^i_{jt+1}, and worker layoff probability s^i_{jt+1} as $\mathbf{\Omega^i_{jt}} = \{w^i_{jt}, d^i_{jt+1}, s^i_{jt+1}, \tilde{W}^i_{jt+1}\}$, where the last three terms are contingent on the firm's next period state variables $(a_{jt+1}, \tilde{P}_{jt}, P_{jt+1}, l_{jt})$ with firm employment size l_{jt} at the end of period t.[17] Firms offer common contracts across

[15]Following the convention in a standard directed search framework, a sufficient statistic to define labor markets is the level of promised utility that each contract delivers to workers upon matching. This is because firms that offer the same utility level to workers compete in the same labor market, and workers that require the same utility level search in the same market.

[16]This is the key to pin down the wage uniquely, which is different from Schaal (2017).

[17]The average productivity $\tilde{P}_{j,-1}$ and the current productivity P_j need to be separate firm state variables as P_j by

workers with the same employment status (ex-post heterogeneity), which makes them offer the same state-contingent next-period variables to workers.[18] Due to the commitment, the firm writes new contracts at t taking as given the utility $\tilde{W}_{jt}$ promised in the previous period for the remaining incumbents at t, and the promised utility x_{jt} for the new hires at t. I drop time subscripts onward.[19]

3.3 The Problems of Workers and Firms

Unemployed workers. Unemployed workers' value function U follows:

$$U = b + \beta \mathbb{E}\Big[\max_{x^{U\prime}} (1 - f(\theta(x^{U\prime})))U' + f(\theta(x^{U\prime}))x^{U\prime}\Big], \tag{5}$$

where b is unemployment insurance and $x^{U\prime}$ is a market they search in, considering a trade-off between the promised utility $x^{U\prime}$ and the job finding probability f as a function of labor market tightness $\theta(x^{U\prime})$.

Employed workers. Employed worker i at firm j have the following value function W^i_j after the search and matching process[20]:

$$\begin{aligned} W^i(a_j, \tilde{P}_{j,-1}, l_{j,-1}, P_j, \mathbf{\Omega^i_j}) = w^i_j + \beta \mathbb{E}_j \Bigg[\Big(\delta + \big(1-\delta\big)\big(d'_j + (1-d'_j)s'_j\big)\Big)U' \\ +(1-\delta)(1-d'_j)(1-s'_j) \max_{x^{E\prime}_j} \Big(\lambda f(\theta(x^{E\prime}_j))x^{E\prime}_j + \big(1 - \lambda f(\theta(x^{E\prime}_j))\big)\tilde{W}'_j\Big)\Bigg]. \end{aligned} \tag{6}$$

This shows that the workers first receive the wage w^i_j as specified in their contracts. For the following period, they consider three possible cases: (i) they are dismissed, either because the

itself directly affects the firm production function, and $\tilde{P}_{jt}$ (the combination of the average productivity $\tilde{P}_{j,-1}$ up to the previous period and the current productivity draw P_j) determines the firm's posterior and future expected value. This will become clear in the following subsection.

[18] i.e., $d^i_{jt+1} = d_{jt+1}, s^i_{jt+1} = s_{jt+1}, \tilde{W}^i_{jt+1} = \tilde{W}_{jt+1}$ for all worker i at the firm in $t+1$. The only source of worker heterogeneity is their employment status (either unemployed or employed, and if employed, where they are employed). Neither worker ex-ante heterogeneity nor human capital accumulation exists. Thus, firms offer the same state-contingent variables to workers (either hired at t or incumbents from t) as the workers get the same status in $t+1$ once joining the firm at t. The current wage at t can vary across them, depending on where they came from $t-1$.

[19] The model can be solved in a recursive form. Superscript $\prime$ denotes the forward period variables at $t+1$, and subscript -1 denotes the previous period variables at $t-1$.

[20] The value function depends on the firm j's state variable $(a_j, \tilde{P}_{j,-1}, l_{jt-1}, P_j)$ as the contract is state-contingent and also depends on $\mathbf{\Omega^i_j}$ as the contract can vary between new hires and incumbents (or even between new hires, depending on their previous employment status).

firm exits (exogenously at rate δ or endogenously if $d'_j = 1$) or because the firm lays off workers with probability s'_j, (ii) they quit and move to other firms by successful search on the job with probability $\lambda f(\theta(x_j^{E\prime}))$, or (iii) they stay in the firm. In the case of firm exit or layoff, workers go to unemployment and get the value U'.[21] $\mathbb{E}_j(\cdot)$ is the workers' expectation of P'_j based on their beliefs on ν_j.

Incumbents. Incumbent firm j ($a_j \geq 1$) has the following problem:

$$J(a_j, \tilde{P}_{j,-1}, l_{j,-1}, P_j, \{\mathbf{\Omega^i_{j,-1}}\}_{i\in[0,l_{j,-1}]}) = \max_{\substack{\{\mathbf{\Omega^i_j}\}_{i\in[0,l_j]},\\ h_j, x_j}} P_j l_j^\alpha - \int_0^{l_j} w_j^i di - c_f$$
$$-\frac{c}{q(\theta(x_j))} h_j + \beta(1-\delta)\mathbb{E}_j\left[(1-d'_j)J(a'_j, \tilde{P}_j, l_j, P'_j, \{\mathbf{\Omega^i_j}\}_{i\in[0,l_j]})\right] \tag{7}$$

at the search and matching stage, subject to:

$$l_j = h_j + (1-s_j)\big(1-\lambda f\big(\theta(x_j^E)\big)\big)l_{j,-1} \tag{8}$$
$$\lambda f(\theta(x_j^{E\prime}))x_j^{E\prime} + (1-\lambda f(\theta(x_j^{E\prime})))\tilde{W}'_j \geq U' \tag{9}$$
$$x_j^{E\prime} = \text{argmax}_x f(\theta(x))\big(x - \tilde{W}'_j\big) \tag{10}$$
$$W(a_j, \tilde{P}_{j,-1}, l_{j,-1}, P_j, \mathbf{\Omega^i_j}) \geq x_j \quad \text{for new hires } i \in [0, h_j] \tag{11}$$
$$W(a_j, \tilde{P}_{j,-1}, l_{j,-1}, P_j, \mathbf{\Omega^i_j}) \geq \tilde{W}_j \quad \text{for incumbent workers } i \in [h_j, l_j], \tag{12}$$

where the firm produces with labor using the decreasing returns-to-scale technology $(\alpha < 1)$, w_j^i is the wage paid to worker $i \in [0, l_j]$ as a component of $\mathbf{\Omega^i_j}$, h_j is the new hires by firm j, x_j is the market firm j chooses, and $q(\theta(x_j))$ and $f(\theta(x_j))$ are the job filling and finding probabilities within the market, respectively, both of which are a function of market tightness $\theta(x_j)$.

(8) is the employment law of motion, (9) is a participation constraint, which prevents workers' return to unemployment unless separations take place, and (10) is an incentive constraint based on incumbent workers' optimal on-the-job search. The firm takes into account their workers' incentive to move to other firms and internalizes the impact of their utility promises on workers' on-the-job search behavior.[22] (11) and (12) are promise-keeping constraints for new hires and

[21] Layoffs are i.i.d. across incumbent workers.

[22] Firms' choice of promised utility to remaining incumbent workers $\tilde{W}'_j$ determines incumbent workers' choice of submarket for on-the-job search $x_j^{E\prime}$ by the incentive condition, and firms take into account this when choosing $\tilde{W}'_j$.

surviving incumbent workers, respectively, under firm commitment. Lemma 1 then follows.

Lemma 1. *Firm promise-keeping constraints* (11) *and* (12) *bind.*

Proof: From (6)*,* (7)*,* (11)*, and* (12)*, each firm j optimally chooses the lowest possible $\{w_j^i\}_i$ that complies with the promise-keeping constraints.*

Entrants. New firms enter each period by paying entry cost c_e after the death shock hits incumbents, but before drawing their initial productivity. They keep entering until the expected value equals the entry cost. After entering and observing their initial productivity, new firms decide whether to stay by paying c_f, search by paying c, hire workers with probability $q(\theta(x_j^e))$ in the market x_j^e they search in, and produce as incumbents.

The entry mass M^e is endogenously determined by the following free entry:

$$\int \max_{\substack{\mathbf{\Omega_j^{ie}}=\{w_j^{ie},d_j',s_j',\tilde{W}_j'\},\\ d_j^e,l_j^e,x_j^e}} (1-d_j^e)\Bigg(P_j(l_j^e)^\alpha - w_j^{ie}l_j^e - c_f - \frac{c}{q(\theta(x_j^e))}l_j^e \tag{13}$$

$$+\beta(1-\delta)\mathbb{E}_j\Big[(1-d_j')J(1,P_j,l_j^e,P_j',\mathbf{\Omega_j^e})\Big]\Bigg)dF_e(P_j) - c_e = 0,$$

where $\mathbf{\Omega_j^{ie}} = \{w_j^{ie}, d_j', s_j', \tilde{W}_j'\}$ is entrant j's contract to worker i; and w_j^{ie}, d_j^e, l_j^e, and x_j^e stand for entrant firm j's wage paid to workers, exit, hiring, and search decisions, respectively, after the firm's initial productivity P_j is observed.[23] Also, the distribution $F_e(P_j)$ of productivity is based on the entrant's initial prior about its own type, and $\mathbb{E}_j(\cdot)$ is the firm's updated posterior after observing P_j. The firm is also subject to the participation and incentive constraints (9) and (10) for retaining incumbent workers in the next period, and the following promise-keeping constraint for new hires in the current period: $W(0,0,0,P_j,\mathbf{\Omega_j^{ie}}) \geq x_j^e$, for all workers $i \in [0, l_j^e]$. Figure 2 outlines the model timeline.

This is key to the unique determination of wages in the absence of worker commitment. Therefore, the number of workers who quit upon successful on-the-job search, $\lambda f(\theta(x_j^E))l_{j,-1}$, is predetermined by the state-contingent utility level $\tilde{W}_j$ that the firm announced in the preceding period and is committed to in the current period.

[23]Note that these terms are a function only of the initial productivity P_j as the entrant does not have any previous history. On the other hand, the last three terms in $\mathbf{\Omega_j^{ie}}$ depend on the entrant's next-period state variables $(1, P_j, l_j^e, P_j')$ after drawing productivity P_j' in the next period.

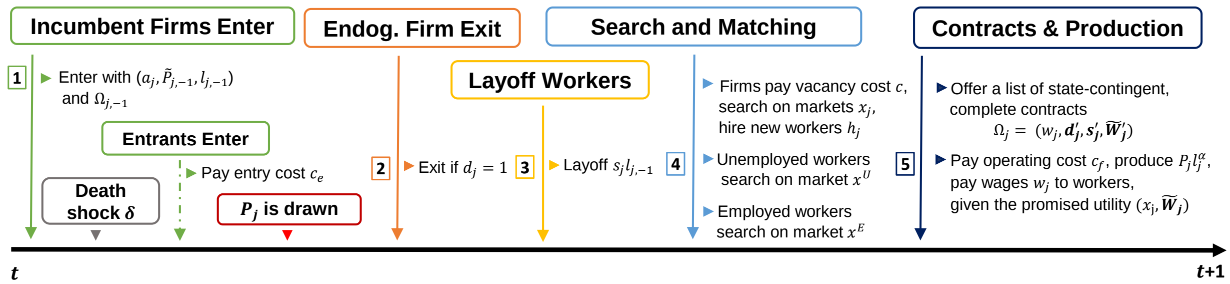

Figure 2: Timeline of the model

3.4 Stationary Recursive Competitive Equilibrium

Equilibrium in each labor market is determined by workers' and firms' optimal search. First, unemployed workers choose a labor market x^U

$$x^U = \text{argmax}_x f(\theta(x))(x - U), \tag{14}$$

with the outside option U given by (5). Employed workers at firm j solve

$$x^E(a_j, \tilde{P}_{j,-1}, l_{j,-1}, P_j) = \text{argmax}_x f(\theta(x))(x - \tilde{W}(a_j, \tilde{P}_{j,-1}, l_{j,-1}, P_j)), \tag{15}$$

taking into account their outside option $\tilde{W}_j$ provided by the current employer j. Equations (14) and (15) determine workers' optimal labor submarkets, where workers consider the trade-off between the value of contract (or unemployment) and the corresponding probability of being matched.[24]

On firms' side, (7) and (13) imply that all firms face the following problem when choosing submarket x_j:

$$x_j = \text{argmin}_x \frac{c}{q(\theta(x))} + x, \tag{16}$$

independent of their state variables. This means that all firms are indifferent across the various submarkets x_j that are solutions to (16). As a result, labor market equilibrium is determined by the

[24]Since ex-post heterogeneity among workers depends on their current employment status, workers' labor market choices will be the same for all workers with a given employment status, either unemployed or employed at a particular firm j with a given set of state variables $(a_j, \tilde{P}_{j,-1}, l_{j,-1}, P_j)$. This implies that the trade-off depends on workers' current employment status (outside option of finding a job).

(possibly multiple) intersections between the decisions of workers and firms (14), (15), and (16).

Let $G(a, \tilde{P}_{-1}, l_{-1})$ be the steady state mass of firms aged a with average log-productivity $\tilde{P}_{-1}$ and size l_{-1} at the beginning of each period. This distribution satisfies the following law of motion:

$$G(a+1, \tilde{P}, l) = (1-\delta) \int_{l_{-1}} \int_{\tilde{P}_{-1}} \Bigg\{ \Big(1 - d\big(a, \tilde{P}_{-1}, l_{-1}, e^{(a+1)\tilde{P} - a\tilde{P}_{-1}}\big)\Big)$$

$$\times \mathbb{I}\big(l(a, \tilde{P}_{-1}, l_{-1}, e^{(a+1)\tilde{P}-a\tilde{P}_{-1}}) = l\big) G(a, \tilde{P}_{-1}, l_{-1}) f_P(e^{(a+1)\tilde{P}-a\tilde{P}_{-1}}) \Bigg\} d\tilde{P}_{-1} dl_{-1}, \text{ for } a \geq 1,$$

$$\text{where } G(1, \tilde{P}_{-1}, l_{-1}) = M^e(1 - d^e(\mathrm{e}^{\tilde{P}_{-1}}))\mathbb{I}\big(l^e(e^{\tilde{P}_{-1}}) = l_{-1}\big) f_P(\mathrm{e}^{\tilde{P}_{-1}}). \tag{17}$$

$\mathbb{I}(\cdot)$ denotes an indicator function, $f_P(\cdot)$ is the probability density function of productivity, M^e is an entry mass, and d^e and l^e are from (13).[25,26]

To close the model, I impose the following labor market clearing condition:

$$\textstyle\sum_{a\geq 1} \int_{\tilde{P}_{-1}} \int_{l_{-1}} \int_P \Bigg\{ \Big(\delta + (1-\delta)\big(d(a, \tilde{P}_{-1}, l_{-1}, P) \tag{18}$$

$$+\big(1 - d(a, \tilde{P}_{-1}, l_{-1}, P)\big) s(a, \tilde{P}_{-1}, l_{-1}, P)\big)\Big) l_{-1} f_P(P) G(a, \tilde{P}_{-1}, l_{-1}) \Bigg\} dP dl_{-1} d\tilde{P}_{-1}$$

$$= f\big(\theta(x^U)\big)\Big(N - \textstyle\sum_{a\geq 1} \int_{\tilde{P}_{-1}} \int_{l_{-1}} l_{-1} G(a, \tilde{P}_{-1}, l_{-1}) dl_{-1} d\tilde{P}_{-1}\Big),$$

where the inflow to the unemployment pool equals the outflow from it.[27]

Definition 1. *A stationary recursive competitive equilibrium consists of: (i) the posteriors on firm types $\{\bar{\nu}_j, \sigma_j^2\}_j$; (ii) a set of value functions U, $\{W_j^i\}_{i,j}$, and $\{J_j\}_j$ for workers and firms; (iii) a decision rule for unemployed workers x^U, for employed workers $\{x_j^E\}_j$, for incumbent firms $\big\{\big(\mathbf{\Omega_j^i} = \{w_j^i, d_j', s_j', \tilde{W}_j'\}\big)_{i\in[0,l_j]}, h_j, l_j, x_j\big\}_j$, and for entrants $\big\{\big(\mathbf{\Omega_j^{ie}} = \{w_j^{ie}, d_j', s_j', \tilde{W}_j'\}\big)_{i\in[0,l_j^e],}, d_j^e, l_j^e, x_j^e\big\}_j$;*

[25] $f_P(P) = \int_\nu f_c(P|\nu) f_\nu(\nu) d\nu$, where f_ν is the pdf of ν, and f_c is the conditional pdf of P given ν.

[26] This defines the next period mass of firms with age $(a+1)$, average log-productivity $\tilde{P}$, and employment size l as the sum of the surviving incumbents of age a that end up having the average log-productivity $\tilde{P}$ from $\tilde{P}_{-1}$, and size $l(a, \tilde{P}_{-1}, l_{-1}, e^{(a+1)\tilde{P}-a\tilde{P}_{-1}}) = l$. Note that the mass of firms with age 1, average productivity $\tilde{P}_{-1}$, and size l_{-1} consists of surviving entrants who have initial productivity $P = \mathrm{e}^{\tilde{P}_{-1}}$ and size $l^e(\mathrm{e}^{\tilde{P}_{-1}}) = l_{-1}$.

[27] The left-hand side of (18) is the total worker inflow to the unemployment pool due to firm exit or layoff from employers with the state (a, $\tilde{P}_{-1}$, l_{-1}, P). The right-hand side is the total outflow from the unemployment pool, which is the number of unemployed workers finding a job. The number of unemployed workers here equals the total population of workers minus the number of employees before firm exit and layoffs due to the timing assumption that workers laid off in a given period cannot search until the next period. Note that there is no loss of workers when entrant firms decide to exit, since entrants that immediately exit never hire workers.

(iv) the labor market tightness $\{\theta(x)\}_x$ for all active markets x; (v) the stationary distribution $G(a, \tilde{P}_{-1}, l_{-1})$; (vi) the entrant mass M^e; such that equations (4)-(18) *are satisfied, given the exogenous process for P, initial conditions $(\bar{\nu}_0, \sigma_0^2)$ and $G(1, \tilde{P}_{-1}, l_{-1})$, and $N = 1$.*

3.5 Main Analytical Results

In this section, I present a set of key analytical results of the model.

Proposition 1. *Equilibrium wages are uniquely determined by workers' employment status (whether unemployed or employed, and the employer's state variables if employed) and their expected future values at the firm. Proof: See the Appendix.*

Lemma 2. *Workers' expected value at a firm decreases in the following order: hiring or inactive firms (no worker quits), firms with worker quits (no hiring), and firms laying off workers or exiting. Proof: See the Appendix.*

The intuition is as follows. After observing firm productivity, the remaining incumbent workers' value is determined by the state-contingent utility $\tilde{W}$ promised by their employer and the workers' target utility in on-the-job search x^E. Taking into account (15), the firm's choice of $\tilde{W}$ depends on its desire to retain workers in the face of potential poaching by other firms.[28] Thus, expanding firms with more willingness to retain workers offer higher values to deter poaching than contracting firms. Also, following (9), workers' value in unemployment is lower than the value of being employed.

Workers therefore expect higher future value at firms that are more likely to hire or retain workers in the next period, as such firms offer greater employment stability and better career trajectories. These firms not only provide higher continuation value but also induce workers to be more ambitious in their on-the-job search, targeting higher outside options. In contrast, firms that are expected to lose workers—due to poaching or layoffs—are perceived as less stable and less willing to sustain high continuation utility, leading workers to anticipate lower future value. As a result, workers' expected future value is increasing in firms' posteriors and in their likelihood of retaining workers. Next, I prove how equilibrium wages vary with firm age.

[28] In the Appendix, I prove in equation (29) that x^E is increasing in $\tilde{W}$ promised by the current employer. In other words, the higher utility $\tilde{W}$ workers obtain from their current firm, the higher utility x^E an outsider firm needs to provide to poach them.

Proposition 2. *Equilibrium wages to a given worker type vary by firm age, even after controlling for other firm observables* $(\tilde{P}_{-1}, l_{-1}, P)$. *Proof: See the Appendix.*

This result shows that wage differentials arise between young firms and otherwise similar mature firms because workers are learning about young firms under limited information.

Proposition 3. *Given the firm state variables* $(\tilde{P}_{-1}, l_{-1}, P)$, *there exists a cutoff for the past-average productivity* $\tilde{P}_{-1}$ *above which equilibrium wage to a given type of workers is higher for younger firms. There also exists a cutoff for* $\tilde{P}_{-1}$ *below which the equilibrium wage is lower for younger firms, all else equal.*[29] *Proof: See the Appendix.*

This implies a nonlinear relationship between firm age and wages. For a given worker type and observable firm characteristics, wage differentials between young and mature firms depend on past-average productivity. In particular, high-performing younger firms (with high past-average productivity $\tilde{P}_{-1}$) pay wage premia relative to observationally similar mature counterparts, while low-performing young firms (with low past-average productivity $\tilde{P}_{-1}$) pay wage discounts relative to their mature counterparts.[30] This stems from the limited information available about younger firms, leading workers to attribute good (bad) past-average performance of young firms less to their actual good (bad) types.[31] If two firms exhibit equally good (bad) performance but differ in age, workers perceive the expected value of being at the younger firm as relatively worse (better) than at the mature counterpart. In the presence of labor market frictions, this generates wage premia (discounts) for high (low)-performing young firms, respectively, all else equal.[32]

[29] Note that the exact cutoffs can only be numerically solved, as will be presented in the following section. Numerical solutions and simulations of the model indicate that the cutoffs generally align with the cross-sectional mean of the past-average productivity $\tilde{P}_{-1}$ or time-invariant productivity type ν.

[30] The equality holds when both firms are mature enough as the posterior converges to the firms' actual type.

[31] This relates to the posterior mean in (4), which is a weighted sum of past-average average performance and initial prior mean with a higher weight put on the average performance for older firms. With older firms having a longer track record, their posterior mean gets closer to the firms' observed performance.

[32] Moreover, if selection leads high-performing firms to dominate low-performing firms, this composition effect can generate an average wage premium for young firms relative to otherwise similar mature firms, consistent with the empirical findings.

Table 3: Calibration

External Calibration			Internal Calibration		
Param.	Description	Value	Param.	Description	Value
β	Time discount rate	0.988	b	Leisure value	1.408
α	Revenue curvature	0.650	λ	OTJ search effic.	0.750
N	Worker mass	1.000	γ	CES parameter	0.720
			c	Vacancy cost	1.718
			c_e	Entry cost	18.81
			δ	Death shock	0.016
			$\bar{\nu}_0$	Initial prior mean	0.590
			σ_0	Initial prior SD	0.733
			σ_ε	Shock SD	0.623
			c_f	Operating cost	2.597

Note: The three parameters in the left panel (β, α, N) are externally calibrated, and the remaining ten parameters in the right panel are internally calibrated to match the set of empirical moments, as discussed in the main text.

4 Quantitative Analysis

4.1 Calibration

I calibrate the model to the U.S. economy on a quarterly basis for 1998Q1-2014Q4. There are thirteen parameters, as listed in Table 3. First, I externally calibrate the first three parameters $\{\beta, \alpha, N\}$ in the left column: I set the discount factor β to 0.99 to match a quarterly interest rate of 1.2%, the production scale α to 0.65 as in Cooper et al. (2007), and normalize the total number of workers $N = 1$.

I internally calibrate the remaining ten parameters $\{b, \lambda, \gamma, c, c_e, \delta, \bar{\nu}_0, \sigma_0, \sigma_\varepsilon, c_f\}$ in the right column to jointly match the following target moments: (i) the unemployment rate, (ii) the employment-employment (EE) rate, (iii) the unemployment-employment (UE) rate, (iv) average firm size, (V) firm entry rate, (vi) the share of young firms, (vii)-(viii) the mean firm productivity at ages 0 and 10 (relative to age 16), and (ix)-(x) the standard deviation of firm productivity at ages 0 and 10.

The following discusses the most relevant moment for each parameter: b is calibrated to the unemployment rate; λ and γ are jointly calibrated to match the EE and UE rates; c is calibrated to target the average firm size; c_e and δ are calibrated to firm entry rate and the share of young firms, respectively; and $\bar{\nu}_0$ and σ_0 calibrated to match the relative mean and standard deviation of (log)

Table 4: Target Moments

Moment	Data	Model	Moment	Data	Model
Unemp rate	0.061	0.058	Young firm share	0.365	0.340
EE rate	0.034	0.037	Mean $\ln P$ ratio $(\frac{age0}{age16})$	0.963	0.939
UE rate	0.244	0.279	SD $\ln P$ (age 0)	0.794	0.776
Average firm size	22.07	23.71	Mean $\ln P$ ratio $(\frac{age10}{age16})$	0.982	0.966
Firm entry rate	0.089	0.089	SD $\ln P$ (age 10)	0.734	0.730

Notes: The table lists the target moments used to calibrate the model. The data sources are the U.S. Bureau of Labor Studies, U.S. Census Bureau, and Haltiwanger et al. (2016).

productivity for startups, while σ_ε and c_f are calibrated to match those of age 10 firms.[33]

The unemployment rate is sourced from the Bureau of Labor Statistics (BLS). The UE rate is measured as the share of unemployed workers who transition to employment in the next period using BLS data, while the EE rate is measured as the share of employed workers who move directly to a new job without an intervening nonemployment spell using the Census Job-to-Job Flows (J2J) database. Average firm size, the firm entry rate, and the share of young firms—defined as firms aged five years or less—are computed from the Census Business Dynamics Statistics (BDS). Mean firm productivity is measured as the relative average log labor productivity of firms at age 0 (or 10) relative to age 16, and the associated standard deviation captures within-industry dispersion in log labor productivity by firm age, using estimates from Haltiwanger et al. (2016).[34] I estimate the model using the simulated method of moments (SMM), minimizing the sum of squared percentage deviations between model-implied moments and their empirical counterparts.

The calibration results are reported in Table 5. Overall, the model fits the targeted moments well. Moreover, it replicates several untargeted moments, including the firm age distribution (left panel of Figure 3) and the life-cycle profile of firm-level productivity dispersion observed in the data (right panel of Figure 3). As shown in Table 5, the calibrated economy also generates employment shares of startups, high-growth firms (defined as DHS employment growth above 0.8), and high-growth young firms of 2.59%, 4.23%, and 3.37%, respectively, closely matching the corresponding data moments of 2.21%, 4.81%, and 3.34%, even though these moments are not targeted in the calibration.

[33] The target moments have mixed frequency in the data. The job flow moments and unemployment rate are measured using quarterly data, while the firm-related moments are estimated using annual data. I calculate model moments using model-implied data at the same frequency as the data counterparts.

[34] The underlying data points were generously shared by Javier Miranda.

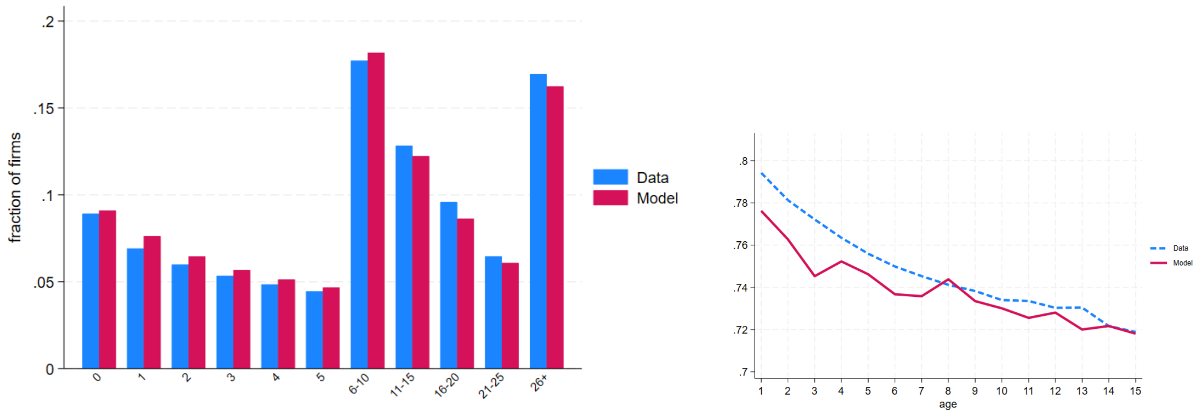

Figure 3: Untargeted Moments: Data vs. Model

Notes: The left panel compares firm age distribution, and the right panel compares the standard deviation of firm productivity across firm age in the model with the data. The data is sourced from BDS 1998–2014 for the firm age distribution and Haltiwanger et al. (2016) for the productivity distribution. The blue bars and dashed line indicate the data moments, and the red bars and solid line present their counterparts in the model.

Table 5: Other Untargeted Moments: Data vs. Model

Moment	Data	Model
Employment Share of Startups	0.022	0.026
Employment Share of high-growth firms	0.048	0.042
Employment Share of high-growth young firms	0.033	0.034

Notes: The table reports a set of untargeted moments that are well matched by the calibrated model. High-growth firms are defined as firms with DHS employment growth above 0.8.

The model also replicates the key empirical patterns in young firms' earnings differentials documented in Section 2. Table 6 shows that young firms pay 2.5% lower wages than mature firms (column 1), with the discount shrinking to 0.8% after controlling for firm size and productivity (column 2). These magnitudes are comparable to the empirical discounts of 4.8% and 1.2% in Table 1, unconditional on worker heterogeneity.[35] Controlling for workers' prior employment status further reduces the discount to 0.2% (column 3), and additionally controlling for firm size and productivity yields a 0.4% wage premium for young firms (column 4). This also mirrors the empirical findings in Table 2. Overall, the model matches the sign and a nontrivial share of the magnitude of the observed earnings differentials, which are untargeted.

[35]The model abstracts from ex-ante worker heterogeneity but allows for ex-post worker heterogeneity through workers' positions along the job ladder. This heterogeneity may still correlate with worker observable characteristics (such as age or skills) in the data, so the model's unconditional specification remains consistent with the empirical counterpart.

Table 6: Wage Differentials for Young Firms

	$\log w$	$\log w$	$\log w$	$\log w$
Young	-0.025***	-0.008***	-0.002***	0.004***
	(0.001)	(0.001)	(0.001)	(0.000)

Notes: The table reports the wage regression results using the simulated model. (The simulation is run for 500 periods, and the model-implied dataset is constructed using observations from the final 100 periods.) The dependent variable is the log wage paid to workers, and the independent variables include dummy variables indicating young firms. The first column does not include any controls, the second column controls for firm size and productivity, the third column controls for the worker's previous employment status (x^U for new hires, $\tilde{W}$ for incumbents), and the last column controls for the worker's previous employment status, firm size, and productivity. Observations are unweighted. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.2 Model Implications for Labor Market Outcomes at Young Firms

The model creates implications on heterogeneous labor market outcomes across firms at different stages of the lifecycle, even conditional on similar observable characteristics. First, I numerically compute wage premia for high-performing young firms and wage discounts for low-performing young firms, as characterized in Proposition 3, using the following specification applied to simulated data from the model:

$$\begin{aligned} w_{it} &= \beta_1 Young_{j(i,t)t} + \beta_2 Young_{j(i,t)t} \times \mathbb{I}^H_{j(i,t)t} + \beta_3 \mathbb{I}^H_{j(i,t)t} + Z_{j(i,t)t}\gamma_1 \\ &\quad + Z_{j(i,t-1)}\gamma_2 + \alpha + \xi_{it}, \end{aligned} \tag{19}$$

where w_{it} is the wages paid to worker i by firm $j(i,t)$ in period t, $Young_{j(i,t)t}$ is an indicator for firms aged five year or less, $\mathbb{I}^H_{j(i,t)t}$ is an indicator for high-performing firms whose past-average productivity or time-invariant type is above the cross-sectional mean, $Z_{j(i,t)t}$ is a vector of firm state variables (past-average productivity, current productivity, and size), and $Z_{j(i,t-1)}$ is the worker's previous employment status, whether being hired from unemployment (or another firm) or retained.

Table 7 reports the results. The first row shows the wage discounts for low-performing young firms, while the second row shows the wage premia for high-performing young firms. Columns 1 and 2 define high-performing firms based on past-average productivity, whereas columns 3 and 4 use time-invariant type. Columns 1 and 3 control for contemporaneous firm size, while columns 2

Table 7: Wage Differentials for Young Firms (High vs. Low-performing)

	$\log w$	$\log w$	$\log w$	$\log w$
Young	-0.010***	-0.011***	-0.015***	-0.017***
	(0.001)	(0.001)	(0.001)	(0.001)
Young $\times$ High performing	0.028***	0.028***	0.034***	0.034***
	(0.001)	(0.001)	(0.001)	(0.001)

Notes: The table reports the wage regression results using the simulated model. (The simulation is run for 500 periods, and the model-implied dataset is constructed using observations from the final 100 periods.) The dependent variable is the log wage paid to workers, and the independent variables include dummy variables indicating young firms, high-performing young firms, and high-performing firms. High-performing firms are defined as those with past-average productivity (columns 1 and 2) or time-invariant type above the cross-sectional mean (columns 3 and 4). Controls include past average productivity, current productivity, and firm employment size, measured with either contemporaneous size (columns 1 and 3) or lagged size (columns 2 and 4). Observations are unweighted. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

and 4 use lagged firm size. Across all specifications, low-performing young firms pay wages that are 1–1.5% lower, while high-performing young firms pay wages that are 1.7–1.9% higher, relative to their similarly-performing older firms for a given worker type.[36] This result offers a structural explanation for the pooled average wage premium of young firms relative to observationally equivalent mature firms (Tables 2 and 6), which arises from selection that disproportionately weights high-performing young firms in the pooled sample.

The model also generates distinct patterns of worker flows across firm age. Figure 4 illustrates the model's implications for high-performing firms, defined as those with past-average productivity $\tilde{P}_{-1}$ above the cross-sectional mean. The figure plots differences between high-performing young and mature firms in workers' expected future values, hiring rates, quit rates, and layoff rates, based on the distribution of each outcome conditional on firm survival.

On average, workers employed at high-performing young firms have lower expected future values than those at otherwise similar mature firms (panel a). Consequently, these firms not only pay higher wages but also face greater difficulty in hiring and retaining workers. In particular, they exhibit lower hiring rates, both unconditionally (panel b) and conditional on positive hiring (panel c), and higher worker outflows, driven by greater poaching risk (panel d) and higher layoff rates (panel e), relative to their mature counterparts.

Similarly, Figure 5 presents the corresponding patterns for low-performing firms with past-

[36] The statistical significance of $\hat{\beta}_1 + \hat{\beta}_2$ is computed by using the delta method.

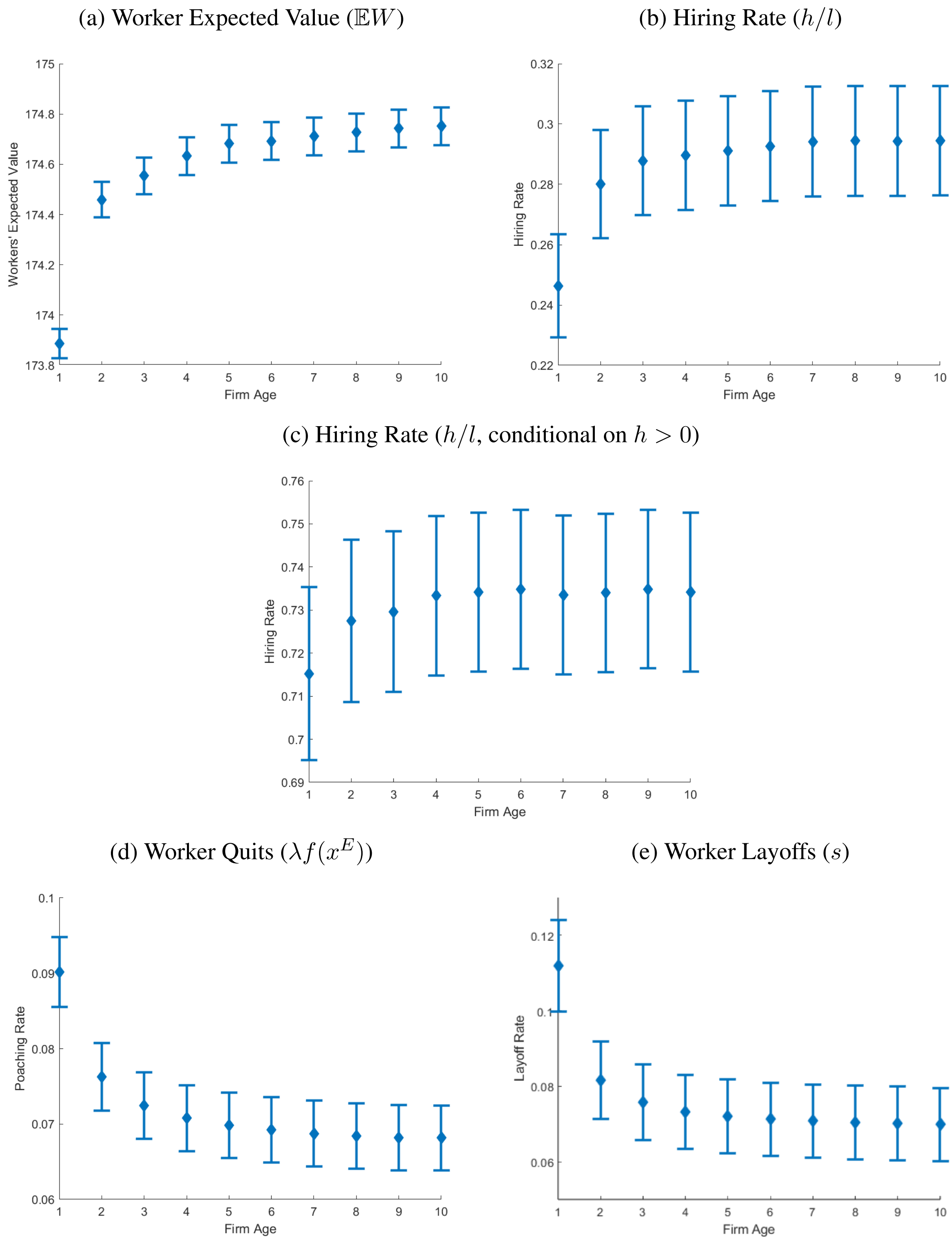

Figure 4: High-performing Firms

Note: This figure shows workers' expected future value (panel a), the rates of hiring (panel b, c), worker quits (panel d), and worker layoffs (panel e) for high-performing firms across different ages. Note that panel c is the hiring rates conditional on positive hiring. The bars denote confidence intervals, and the dots indicate the cross-sectional means of each variable, conditional on firm age.

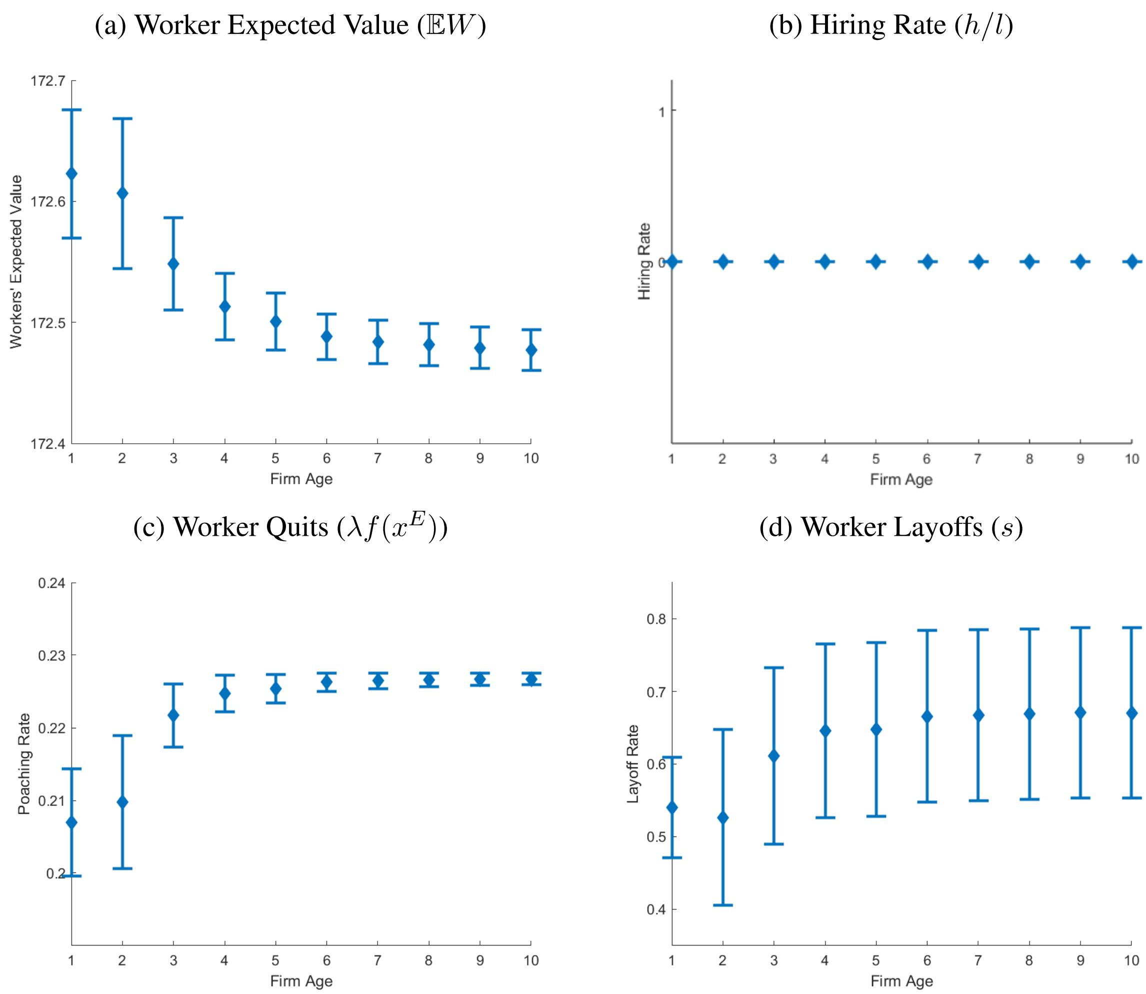

Figure 5: Low-performing Firms

Note: This figure shows workers' expected future value (panel a), the rates of hiring (panel b), worker quits (panel c), and worker layoffs (panel d) for low-performing firms across different ages. The bars denote confidence intervals, and the dots indicate the cross-sectional means of each variable, conditional on firm age.

Table 8: Counterfactual Exercises

Description	Baseline	No Learning	No Search
Panel A: Changes in Firm Dynamics			
Firm entry rate	0.089	0.105	0.190
Share of young firms	0.340	0.384	0.442
Employment Share of startups	0.026	0.055	0.079
Employment Share of young firms	0.233	0.288	0.307
Share of high-growth young firms	0.097	0.120	0.217
Employment share of high-growth young firms	0.033	0.085	0.257
Panel B: Changes in Productivity Distribution (All)			
Aggregate productivity	2.435	2.576	3.441
p50 firm productivity	2.434	2.550	3.488
p90 firm productivity	3.441	3.678	4.328
Panel B: Changes in Productivity Distribution (Young Firms)			
Aggregate productivity of young firms	2.421	2.559	3.363
p50 young firm productivity	2.427	2.539	3.399
p90 young firm productivity	3.458	3.676	4.286

Notes: This table reports counterfactual results under no learning frictions (column 2) and no search frictions (column 3). Startups are defined as firms aged one year or less, young firms as those aged five years or less, and high-growth firms as those with DHS employment growth above 0.8 in a given period. Aggregate productivity is measured as the employment-share–weighted average of firm-level log productivity. Each model is simulated for 500 periods, and statistics are computed using data from the final 100 periods.

average productivity $\tilde{P}_{-1}$ below the cross-sectional mean. On average, Workers employed at low-performing young firms have higher expected future values than those at otherwise similar mature firms (panel a), leading these firms to offer lower equilibrium wages. Consistent with this, low-performing young firms exhibit lower worker outflows, driven by lower poaching risk (panel c) and lower layoff rates (panel d), relative to their mature counterparts. Note that these firms rarely expand and typically exhibit zero hiring due to their low productivity (panel b). These patterns are consistent with Proposition 3 and arise from the interaction of learning and labor market frictions.

4.3 Counterfactual Analysis

Labor market outcomes in the model are shaped by two frictions: (i) information frictions faced by young firms and (ii) labor market frictions. I quantify the contribution of each friction to firm dynamics and aggregate outcomes by conducting counterfactual exercises that remove each friction.

Table 8 reports the results. Panel A shows that reductions in information frictions (column

2) and search frictions (column 3) both stimulate firm entry and young-firm activity, with effects markedly stronger under the removal of search frictions. Relative to the baseline, the firm entry rate rises by 18% under no information friction and more than doubles under no search friction. The employment share of young firms increases by 5.5 percentage points under no learning and by 7.4 percentage points under no search friction. In particular, both the share and the employment share of high-growth young firms—defined as young firms with DHS employment growth exceeding 0.8 in a given period—increase.[37] Their employment share rises from 3.3% in the baseline to 8.5% under no learning and to 25.7% under no search friction, indicating a strong amplification of reallocation toward fast-growing young firms when labor market frictions are relaxed.

Panel B shows that these changes are accompanied by substantial rightward shifts in the productivity distribution, with higher-productivity firms expanding relative to the baseline. Aggregate productivity increases by about 6% under no learning and by 41% under no search friction. Gains are concentrated in the upper tail: the top decile in firm (log) productivity rises from 3.44 in the baseline to 3.68 under no learning and to 4.33 under no search friction. Panel C shows analogous patterns among young firms, with aggregate productivity increasing by 5.7% under no learning and by 39% under no search frictions, and the largest gains driven by the top decile of high-productivity young firms. Overall, reductions in both frictions substantially promote entry, reallocation, and productivity, primarily through the expansion of high-growth young firms. Quantitatively, the effects are markedly stronger under reductions in search frictions.

The underlying intuition is straightforward: both factors reduce wage differentials for young firms. First, as information friction is removed, there is no longer a gap between young and mature firms of workers' future expected value, and thus the wage differentials along the lifecycle, conditional on firm performance, are removed. This goes back to the set up in Schaal (2017). Second, search frictions operate through a distinct but complementary channel. When labor mobility is limited, workers internalize the risk of being locked into bad firms and therefore place greater weight on future prospects when accepting job offers under limited information. Reducing search frictions relaxes this constraint by facilitating worker reallocation across firms, which mitigates workers' concerns about future job prospects even when information about young firms remains imperfect. In equilibrium, this compresses wage differentials across firm ages.

[37] This cutoff is held fixed to ensure a consistent comparison across counterfactuals.

Through this interaction, search frictions amplify the effects of information frictions on young firms. When either friction is removed, wage differentials are eliminated, allowing high-performing young firms to survive and expand more effectively, while low-performing young firms contract and exit more rapidly. This selection reallocates employment toward more productive firms and raises aggregate productivity.

5 Empirical Supporting Evidence

In this section, I test the model's predictions using administrative firm-level and matched employer–employee data from the U.S. Census Bureau, described in Section 2.1. First, I estimate the firm productivity process and isolate the component of productivity from which firms and workers learn about firm fundamentals. Second, I classify firms as high- or low-performing based on whether their cumulative average productivity lies above or below the within-industry cross-sectional mean, and test whether young high- (low-) performing firms pay wage premia (discounts) relative to mature counterparts. Third, I measure uncertainty using within-industry cross-sectional dispersion in firm productivity fixed effects and residuals and examine its effect on wage differentials, aggregate firm dynamics and productivity. Finally, I proxy labor market frictions using sector-level job mobility and assess its relationship with aggregate firm dynamics and productivity.

5.1 Main Measures

First, I estimate the firm-type learning process in the data as follows:

$$\ln P_{jt} = \rho \ln P_{jt-1} + \nu_j + \varepsilon_{jt}, \tag{20}$$

where I project log real revenue productivity for firm j demeaned at the industry-year level on its own lag by taking out firm fixed effect ν_j.[38] Note I remove industry-year means to control for industry-specific differences, time trends or cyclical shocks, and include the lag term $\ln P_{jt-1}$ to account for productivity persistence not captured by the model. The remaining terms are denoted

[38] To address potential endogeneity bias in a dynamic panel model with the lagged dependent variable, I adopt the Generalized Method of Moments (GMM) estimator in Blundell and Bond (1998).

by $\ln \hat{P}_{jt} \equiv \hat{\nu}_j + \hat{\varepsilon}_{jt}$, which I use to map into the model productivity.[39]

Next, I construct the average of $\hat{P}_{jt}$ over the firm life-cycle for each firm using longitudinal firm identifiers, denoted as: $\tilde{P}_{jt-1} \equiv \frac{\sum_{\tau=t-a_{jt}}^{t-1} \ln \hat{P}_{j\tau}}{a_{jt}}$, where a_{jt} is the age of firm j in year t. To track the accumulation of firm performance and the learning process in each period properly, I limit the sample to firms that have consecutively non-missing observations of $\ln \hat{P}_{jt}$ from their birth.[40] I use $\ln \hat{P}_{jt}$ and $\tilde{P}_{jt-1}$ in my regression below as measures representing contemporaneous productivity and past-average productivity, respectively. I define high-performing firms as those with average productivity above the industry mean of estimated prior mean, i.e., $\tilde{P}_{jt-1} > \frac{\sum_{j \in g(j,t)} \hat{\nu}_j}{N_{g(j,t)}}$ where $N_{g(j,t)}$ is the number of firms in industry $g(j,t)$ and year t.[41]

To capture the two types of frictions, I construct the following measures. First, I proxy information frictions using industry-level uncertainty, defined as

$$Uncertainty_{gt} \equiv \frac{\hat{\sigma}_{\varepsilon gt}}{\hat{\sigma}_{0gt}}, \tag{21}$$

where $\hat{\sigma}_{\varepsilon gt}$ and $\hat{\sigma}_{0gt}$ are the cross-sectional dispersion of $\hat{\varepsilon}_{jt}$ and $\hat{\nu}_j$, respectively, estimated from (20) within industry g and time t. This is known as the "noise-to-signal" ratio. Second, I proxy labor market frictions using sector-level worker mobility, measured by the Nonemployment-to-Employment (NE) and Employment-to-Employment (EE) transition rates in the Census J2J database.

5.2 Earnings Differentials Implied by Learning

To test the learning mechanism in the model, I run the following regression:

$$\begin{aligned} \hat{\epsilon}_{it} = & \beta_1 Young_{j(i,t)t} + \beta_2 Young_{j(i,t)t} \times \mathbb{I}^H_{j(i,t)t} + \beta_3 \mathbb{I}^H_{j(i,t)t} + Z_{j(i,t)t}\gamma_1 \\ & + Z_{j(i,t-1)}\gamma_2 + \mu_{g(j(i,t))} + \mu_{s(j(i,t))} + \alpha + \xi_{it}, \end{aligned} \tag{22}$$

[39] The underlying assumption is that firms and workers can observe the industry-by-time means as well as the persistence in the firm-level productivity process, and filter these out when estimating the firm's fundamental. Therefore, they infer a firm's type using the remaining terms, which reflect the firm-level fixed effect ν_j and the residual ε_{jt}.

[40] This is the main sample with summary statistics shown in Online Appendix D.3.

[41] This classification is guided by the model's numerical results. As robustness checks, I use alternative thresholds to define high-performing firms, including the within-industry cross-sectional median, the 75th percentile, and the within-industry cohort mean of the estimated prior mean productivity. I also alternatively set thresholds using the mean of past-average productivity. The results are robust and available upon request.

where $\hat{\epsilon}_{it}$ denotes earnings residuals estimated from (2), which net out worker heterogeneity, $j(i,t)$ indexes the employer of worker i at time t, $Young_{j(i,t)t}$ is an indicator for young firms, $\mathbb{I}^H_{j(i,t)t}$ is an indicator for high-performing firms, $Z_{j(i,t)t}$ is a vector of firm $j(i,t)$'s characteristics, including past-average productivity, current productivity, and employment size (as in the model), and $Z_{j(i,t-1)}$ contains controls for the worker's employment status in the previous period.[42] As before, I use the AKM firm fixed effect associated with the worker's previous employer along with a non-employment indicator as a baseline.[43] Industry (g) and state (s) fixed effects, $\mu_{g(j(i,t))}$ and $\mu_{s(j(i,t))}$, are also included.

The novelty in (22) comes from β_1 and β_2, which capture how firms with a given set of observable characteristics pay differently by firm age, and how this age effect varies with the firm's average performance over past periods. For low-performing firms, the wage differential for young firms is given by β_1, while for high-performing firms it is given by $\beta_1 + \beta_2$.

Table 9 shows the results with the full set of controls to be consistent with the model.[44] Column 1 controls for contemporaneous firm size, and column 2 uses lagged firm size. The estimates show that $\hat{\beta}_1 < 0$, $\hat{\beta}_2 > 0$, and $\hat{\beta}_1 + \hat{\beta}_2 > 0$, with all point estimates statistically significant.[45] Quantitatively, high-performing young firms pay wages that are 1.3% higher than otherwise similar mature firms, whereas low-performing young firms pay wages that are 0.3% lower on average. These are consistent with the model predictions in Section 4.2.

To validate the baseline results, I conduct several robustness checks, reported in Online Appendix F. First, because firm size is highly correlated with firm age and may absorb age-related effects, I re-estimate the regressions excluding firm size. The results remain robust (Online Appendix Table F1). The second test addresses potential sampling bias by applying inverse propensity score weights (Online Appendix Table F2). Third, the second-stage regression is based on estimates from the first-stage regression, which might cause the reported standard errors in Table

[42]Note that firm fixed effects are retained in the earnings residuals as proxies for unobserved firm fundamentals that workers gradually learn. As a robustness check, I also follow Abowd et al. (1999) by recovering firm effects using the sum of estimated firm fixed effects and residuals. This approach relies on exogenous worker mobility, which may be violated if workers sort into firms based on unobserved characteristics; in that case, the residual may still reflect sorting rather than pure worker productivity.

[43]The baseline AKM firm fixed effects are estimated at the SEIN (State Employer Identification Number) level, and firm-level variables take identical values for all workers employed at the same firm at time t. As robustness checks, I alternatively use firm fixed effects estimated at the firm-identifier level or earnings paid by the previous employer.

[44]For brevity, only the main coefficients are reported, with full results presented in Online Appendix Table E1.

[45]The statistical significance of $\hat{\beta}_1 + \hat{\beta}_2$ is computed by using the delta method.

Table 9: Wage Differentials for Young Firms

	Earnings Residuals	Earnings Residuals
Young	-0.002***	-0.003***
	(0.001)	(0.001)
Young $\times$ High performing	0.015***	0.016***
	(0.001)	(0.001)
Observations	50,170,000	50,170,000
Fixed effects	g, s	g, s
Controls	Full (current size)	Full (lagged size)

Notes: The table reports the main earnings regression results. Firm controls include past-average productivity, current productivity, and log employment size. Controls associated with worker's previous employment status are the AKM firm fixed effect associated with the previous employer and a dummy for non-employed workers in the previous period. Observation counts are rounded to the nearest 10,000 to avoid potential disclosure risks. Estimates for constant, industry, state fixed effects, the coefficient of the indicator for worker's previous non-employment status are suppressed. Observations are unweighted. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

9 to be incorrect. To address this, I estimate the standard errors with bootstrapping and confirm the robustness of the statistical significance (Online Appendix Table F3). Fourth, alternative interpretations of the results may arise from other potential sources related to unobserved time-varying worker characteristics. For instance, high-performing young firms may demand experienced workers with longer tenure than mature counterparts given the burden of training costs, which may result in the earnings premia. I confirm the robustness after controlling for earnings in the previous job as a proxy of worker tenure or experience (Online Appendix Table F4). Worker skills may also affect earnings. To address this, I use workers' highest education level as a proxy for skills, include it as an additional control in the first-stage regression, and confirm robustness in the second-stage estimates (Online Appendix Table F5). Another potentially unobserved worker characteristic is risk preference. Unobserved risks in young firms may still remain even after controlling for firm characteristics, in which case the currently estimated young-firm effects could reflect worker sorting based on risk preferences. I address this concern by additionally controlling for the variance of young-firm productivity shocks as a proxy for firm riskiness (Online Appendix Table F6). In addition, I confirm robustness using firm fixed effects estimated with longitudinal firm identifiers (Online Appendix Table F7). Finally, I re-estimate the regression at the firm level using firm-level averages of earnings residuals and the same set of firm controls (Online Appendix Table F8).[46]

[46]This result indicates that averaging earnings differentials across worker types and employment histories preserves

Table 10: Wage Differentials for Young Firms (High-tech only)

	Earnings Residuals	Earnings Residuals
Young	-0.016***	-0.015***
	(0.005)	(0.001)
Young × High performing	0.034***	0.035***
	(0.006)	(0.006)
Observations	1,203,000	1,203,000
Fixed effects	g, s	g, s
Controls	Full (current size)	Full (lagged size)

Notes: The table reports the main earnings regression results in high-tech sectors (NAICS 334 and 51). All else follows the same as in Table 9. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The baseline results mask substantial heterogeneity across environments, such as industries. To further examine how the earnings differentials vary across different environments, I focus on high-tech sectors (NAICS 334 and 51). These sectors have been key drivers of job creation and productivity growth, with particularly active transformational entrepreneurship (Decker et al., 2016). The results show even larger earnings differentials in these sectors, as reported in Table 10.[47] Specifically, in high-tech sectors, low-performing young firms pay earnings that are 1.5% lower, while high-performing young firms pay earnings that are approximately 2% higher, relative to otherwise similar mature firms. This pattern suggests that the learning mechanism is more pronounced in high-tech sectors, where young firm activity plays an important role in the aggregate economy.

5.3 Earnings Differentials and Firm Outcomes

Next, I examine the relationship between earnings differentials and firm outcomes (hiring or employment growth), using the following specification:

$$Y_{jt} = \beta \hat{\epsilon}_{jt} + Z_{jt}\gamma + \mu_{g(j,t)} + \mu_{s(j,t)} + \alpha + \xi_{jt}, \tag{23}$$

where Y_{jt} is either the number of new hires or employment growth of firm j, $\hat{\epsilon}_{jt}$ denotes the average earnings residuals, averaging $\hat{\epsilon}_{it}$ across workers i at firm $j(i,t)$, Z_{jt} is a vector of firm controls (age,

the qualitative findings. This pattern is consistent with the model, in which firms randomly select workers along an indifference curve and firm-level earnings differentials move in the same direction as worker-level earnings after conditioning on worker heterogeneity.

[47] For space considerations, the full set of results are reported in Online Appendix Table E2.

Table 11: The Effect of Wage Differentials on Firm Outcomes

	Hire (firm)	Hire (SEIN)	ΔEmp (Δlog)	ΔEmp (DHS)
Earnings Residuals	-0.520***	-0.387***	-0.015***	-0.018***
	(0.020)	(0.024)	(0.000)	(0.000)
Observations	6,959,000	6,959,000	6,959,000	6,959,000
Fixed effects	g, s	g, s	g, s	g, s
Controls	P, size, age	P, size, age	P, size, age	P, size, age

Notes: The table reports the effect of earnings residuals on firm-level outcomes. Firm controls include firm productivity, log employment size, and age. New hires are either the firm-level total new hire (column 1) or the average of the SEIN-level new hires (column 2). Employment growth is either the log-difference (column 3) or the DHS growth (column 4) of firm employment size. Observation counts are rounded to the nearest 10,000 to avoid potential disclosure risks. Estimates for constant, and industry (g), state (s) fixed effects are suppressed. Observations are unweighted. * $p < 0.1$, ** $p < 0.05$, $p < 0.01$.

size, and productivity), and $\mu_{g(j,t)}$ and $\mu_{s(j,t)}$ are industry and state fixed effects, respectively.

Table 11 shows the results, indicating a negative association between earnings residuals and both firm hiring and employment growth, independent of firm age, size, and productivity effects.[48] The estimated coefficients indicate that a 1% increase in the firm-level earnings residuals is associated with a 1.8 (1.5) percentage point decrease in the DHS employment growth rate (the log-difference of employment) at the firm level. This supports interpreting earnings differentials as stemming from the learning channel, ruling out other hypotheses such as performance pay or surplus sharing. The results are robust to applying inverse propensity score weights or using $\hat{P}_{jt}$ estimated in (20), as shown in Online Appendix G.

5.4 The Effect of Uncertainty on Earnings Differentials

In the model, wage and labor market differentials between young firms and otherwise similar mature firms vanish in the absence of information frictions and learning. Conversely, when learning slows under greater uncertainty, these differentials become more pronounced. To test this, I include additional interaction terms with the industry-level uncertainty (21) in (22):

$$\hat{\epsilon}_{it} = \beta_1 Young_{j(i,t)t} + \beta_2 Young_{j(i,t)t} \times \mathbb{I}^H_{j(i,t)t} + \beta_3 Young_{j(i,t)t} \times Uncertainty_{g(j,t)t}$$

[48] Due to space constraints, the full results are available in Online Appendix Table E3.

Table 12: The Effect of Uncertainty on Young Firms' Wage Differentials

	Earnings Residuals	Earnings Residuals
Young firm	-0.001	-0.001
	(0.001)	(0.002)
× Uncertainty	-0.004**	-0.005**
	(0.002)	(0.002)
Young firm × High performing	0.012***	0.003
	(0.002)	(0.002)
× Uncertainty	0.006***	0.016***
	(0.002)	(0.003)
Observations	50,170,000	50,170,000
Fixed effects	g, s	g, s
Controls	Full (current size, current uncertainty)	Full (current size, lagged uncertainty)

Notes: The table reports the earnings regression interacted with industry-level uncertainty. The first column is based on the current value of uncertainty, and the second column os based on the lagged value. The set of controls and fixed effects remain the same as in the baseline regression (22). Observation counts are rounded to the nearest 10,000 to avoid potential disclosure risks. Estimates for constant, fixed effects, the coefficient of the indicator for worker's previous non-employment status are suppressed. Observations are unweighted. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

$$+ \beta_4 Young_{j(i,t)t} \times \mathbb{I}^H_{j(i,t)t} \times Uncertainty_{g(j,t)t} + \beta_5 Uncertainty_{g(j,t)t} + \beta_6 \mathbb{I}^H_{j(i,t)t}$$
$$+ \beta_7 \mathbb{I}^H_{j(i,t)t} \times Uncertainty_{g(j,t)t} + Z_{j(i,t)t}\gamma_1 + Z_{j(i,t-1)}\gamma_2 + \mu_{g(j(i,t))} + \mu_{s(j(i,t))}$$
$$+ \alpha + \xi_{it},$$

where I use firm $j(i,t)$'s main industry $g(j,t)$ in t for the uncertainty, and $\mu_{g(j(i,t))}$ is sector (NAICS2) fixed effects.[49] To mitigate potential reverse causality issue, I use both current and lagged values of uncertainty. All else is the same as in (22).

Table 12 presents the results, with the current value of uncertainty in the first column and the lagged value in the second column. Both show that as uncertainty rises, there are more pronounced earnings premia for high-performing young firms ($\hat{\beta}_3 + \hat{\beta}_4 > 0$) and discounts for low-performing young firms ($\hat{\beta}_3 < 0$).[50] This holds for both columns. The estimated coefficient implies that a one standard deviation increase in uncertainty (0.161) leads to a 17.35% increase in earnings premia for high-performing young firms, and a 17.02% increase in earnings discounts for low-

[49]This allows for variations in uncertainty across industries while controlling for fundamental differences across sectors.

[50]Again, delta method is applied for the statistical significance of all interaction terms.

Table 13: Aggregate Implications of Uncertainty

	Entry rate	Young firm share	High-growth young firm share	High-growth young firm growth	Productivity
Uncertainty	-0.009***	-0.013***	-0.010***	-0.020***	-0.227***
	(0.002)	(0.005)	(0.003)	(0.005)	(0.011)
Observations	4,300	4,300	4,300	4,300	4,300
Fixed effects	g, t	g, t	g, t	g, t	g, t

Notes: The table reports results for regression of the firm entry, share of (high-growth) young firm, average growth of high-growth young firms, and aggregate productivity in each column on industry-level uncertainty in (21), with industry (g) and year (t) fixed effects controlled. Observation counts are rounded to the nearest 100 to avoid potential disclosure risks. Estimates for constant and fixed effects are suppressed. Observations are unweighted. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

performing young firms, relative to their otherwise similar old counterparts, in an industry with average uncertainty (0.743). In the Online Appendix, Table E4 presents the full results, and Table F9 shows its robustness by controlling lagged firm size instead of contemporaneous size.

5.5 Aggregate Implications

Lastly, I provide empirical evidence supporting the aggregate implications of learning and labor market frictions for firm dynamics. I begin by examining how information frictions are associated with aggregate industry-level outcomes using the following specification:

$$Y_{gt} = \beta Uncertainty_{gt} + \delta_g + \delta_t + \epsilon_{gt}, \tag{24}$$

where Y_{gt} denotes the firm entry rate, the share of young firms or high-growth young firms, the average employment growth of high-growth young firms, or average productivity in industry g and year t.[51] δ_g and δ_t denote industry and year fixed effects, respectively.

Table 13 shows that aggregate firm dynamics and productivity are dampened in industries with higher uncertainty (indicative of noisier learning), where earnings differentials for young firms are amplified in the earlier results. In particular, this indicates that a one–standard-deviation increase in uncertainty is associated with a 0.161 percentage point reduction in the share of high-growth young firms and a 0.321 percentage point decline in their average employment growth. The results

[51] High-growth young firms are defined as firms aged five years or less whose employment growth lies above the 90th percentile of the within-industry distribution.

Table 14: Aggregate Implications of Uncertainty

	Entry rate	Young firm share	Young firm emp. share	High-growth young firm share	High-growth young firm emp. share
Job Mobility	0.195***	0.369***	0.598***	0.299***	0.274***
	(0.048)	(0.126)	(0.079)	(0.055)	(0.031)
Observations	418	418	418	418	418
Fixed effects	g, t	g, t	g, t	g, t	g, t

Notes: The table reports results for regression of the firm entry, share and employment share of (high-growth) young firm in each column on sector-level (NAICS2) job mobility rate, with sector (g) and year (t) fixed effects controlled. Estimates for constant and fixed effects are suppressed. Observations are unweighted. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

are qualitatively similar in the long run—using industry fixed effects to align with the model's steady-state economy—as shown in Online Appendix H.

Furthermore, I also examine the interaction between labor market mobility and aggregate firm dynamics with the following regression:

$$Y_{gt} = \beta JobMobility_{gt} + \delta_g + \delta_t + \varepsilon_{gt}, \tag{25}$$

where JobMobility_{gt} is the rate of nonemployment-to-employment (NE) and employment-to-employment (EE) transitions, capturing worker mobility in sector g and year t. Table 14 reports the results, showing that sectors with higher job mobility (indicative of less frictional labor markets) exhibit more active young-firm dynamics. These findings support the model's aggregate implications.

6 Conclusion

In this paper, I study how workers' job prospects determine wages and growth at young firms, worker allocation across firms, and aggregate firm dynamics and productivity. I develop a model of firm dynamics with learning about firm fundamentals and labor market frictions, and discipline it using micro-level administrative data. I show that workers' learning under labor market frictions generates systematic wage differentials and distinct labor market outcomes for young firms: high-performing young firms pay wage premia and exhibit lower hiring rates and higher worker outflows, whereas low-performing young firms pay wage discounts, relative to observationally equivalent mature firms. Reductions in information or labor market frictions attenuate these gaps and stimulate the growth of high-performing young firms, thereby raising aggregate productivity. Overall, the paper highlights workers' job prospects as a novel mechanism jointly shaping firm dynamics and labor market outcomes and provides a unified framework for understanding heterogeneity in firm dynamics across different economic environments.

Appendix: Proofs of Propositions

***Proof of Proposition 1*.** Lemma 1 can rephrase (11) and (12):

$$w_j^i = x_j - \beta \mathbb{E}_j \Bigg[\Big(\delta + (1-\delta)\big(d_j' + (1-d_j')s_j'\big) \Big) U$$
$$+(1-\delta)(1-d_j')(1-s_j')\Big(\lambda f(\theta(x_j^{E\prime}))x_j^{E\prime} + \big(1-\lambda f(\theta(x_j^{E\prime}))\big)\tilde{W}_j' \Big) \Bigg] \tag{26}$$
$$w_j^i = \tilde{W}_j - \beta \mathbb{E}_j \Bigg[\Big(\delta + (1-\delta)\big(d_j' + (1-d_j')s_j'\big) \Big) U$$
$$+(1-\delta)(1-d_j')(1-s_j')\Big(\lambda f(\theta(x_j^{E\prime}))x_j^{E\prime} + \big(1-\lambda f(\theta(x_j^{E\prime}))\big)\tilde{W}_j' \Big) \Bigg]. \tag{27}$$

The first term on the right hand side of (26) and (27) shows the promised utility for new hires and incumbent workers, which is determined by the worker's previous employment status in equilibrium. The large bracket on the right hand side is the worker's future expected value at the firm.

Firms choose submarkets satisfying (16), where the complementary slackness condition holds for any active labor submarket x, $\theta(x)\left(\frac{c}{q(\theta(x))} + x - \kappa\right) = 0$, with the minimized cost $\kappa \equiv \min\left(\frac{c}{q(\theta(x))} + x\right)$. With this, the promised utility for new hires, $x_j \in \{x^U, \{x_k^E\}_k\}$, is determined by the workers' optimal choice of labor markets in their search as follows:

$$x^U = \kappa - (c^\gamma(\kappa - U))^{\frac{1}{1+\gamma}} \tag{28}$$
$$x_k^E(a_k, \tilde{P}_{k,-1}, l_{k,-1}, P_k) = \kappa - (c^\gamma(\kappa - \tilde{W}_k(a_k, \tilde{P}_{k,-1}, l_{k,-1}, P_k)))^{\frac{1}{1+\gamma}} \tag{29}$$

for unemployed workers and employed workers at k, respectively, with the CES matching function. Notably, the choice of labor market for both worker types only depend on their employment status in the search process and its value (U or $\tilde{W}_k$), but not on recruiting firm j's characteristics.[52,53] Furthermore, due to workers' non-commitment, employers (j) take into account (29) when offering $\tilde{W}_j$ to their incumbent workers. Thus, $\tilde{W}_j$ (and thus x_j^E) is uniquely pinned down from the firm's maximization, from which the equilibrium wage can uniquely be backed out from (26) and (27).[54]

□

Proof of Lemma 2 . The equilibrium labor submarkets are determined by:

$$\theta(x) = \begin{cases} \left(\left(\frac{\kappa - x}{c}\right)^{\gamma} - 1\right)^{\frac{1}{\gamma}} & \text{if} \quad x < \kappa - c \\ 0 \quad \text{if} \quad x \geq \kappa - c, \end{cases} \tag{30}$$

where $\theta'(x) < 0$, and no firms post vacancies if $x \geq \kappa - c$, i.e., $\theta(x) = 0$.

Solving other choice variables of firms, the firm problem in (7)-(12) can be fully replicated by the following joint surplus maximization:

$V^{init}(a_j, \tilde{P}_{j,-1}, l_{j,-1}, P_j) = \max_{d_j, s_j, h_j, x_j^E} \delta U l_{j,-1} + (1-\delta)(d_j + (1-d_j)s_j)U l_{j,-1} + (1-\delta)(1-d_j)\Big(P_j l_j^{\alpha} - c^f - \kappa h_j + (1-s_j)\lambda f(\theta(x_j^E)) x_j^E l_{j,-1} + \beta \mathbb{E}_j V^{init}(a_j', \tilde{P}_j, l_j, P_j')\Big)$, where V_j^{init} is the joint surplus at the beginning of the period.[55]

There are four endogenous productivity cutoffs $\mathcal{P}_j \equiv \mathcal{P}_j(a_j, \tilde{P}_{j,-1}, l_{j,-1})$ among operating firms: i) the upper cutoff $\mathcal{P}_j^h$ between hiring and inaction without quits; ii) the middle cutoff $\mathcal{P}_j^q$ between inactions without or with quits; iii) the lower cutoff $\mathcal{P}_j^l$ between inaction with quits and layoffs; and iv) the exit cutoff $\mathcal{P}_j^x$ below which firms endogenously exit.[56]

[52] Workers search in a submarket offering a utility at least equal to their current value, U for unemployed workers and $\tilde{W}_k$ for employed workers, unlike firms that are indifferent across submarkets.

[53] The market unemployed workers search in x^U is constant with respect to firms' state variables as unemployed workers have no heterogeneity (both ex-ante and ex-post) and thus all choose the same market to search. Employed workers' choice (x_k^E) depends on the utility offered by their current employer k ($\tilde{W}_k$), which varies with the employer k's state. The higher utility $\tilde{W}_k$ workers receive from their current employer k, the higher utility x_k^E a hiring firm j needs to provide to poach them successfully. Workers only climb up to a labor market that provides higher utility than their current one, reflecting the job ladder property.

[54] Workers' non-commitment condition is important for this property. If workers cannot leave a firm with full commitment, then wages as well as the promised utility won't be uniquely determined as in Schaal (2017).

[55] More details are provided in Online Appendix B. Similarly, (13) can be rephrased as $\int \max_{d_j^e, l_j^e}(1-d_j^e)\Big(P_j(l_j^e)^{\alpha} - c^f - \kappa l_j^e + \beta \mathbb{E}_j V^{init}(1, \ln P_j, l_j^e, P_j')\Big) dF_e(P_j) - c^e = 0$.

[56] These cutoffs are generated due to vacancy cost and operating fixed cost and endogenously determined by the state variables $(a_j, \tilde{P}_{j,-1}, l_{j,-1})$ before the contemporaneous productivity draw P_j. See details in Online Appendix C.

The first-order conditions with respect to h_j, s_j, and x_j^E are as follows:

$$\left[\alpha P_j l_j^{\alpha-1} + \beta \frac{\partial \mathbb{E}_j V_j^{init\prime}}{\partial l_j}\right] - \kappa = 0, \tag{31}$$

$$U l_{j,-1} - \lambda f(\theta({x_j}^E)) x_j^E l_{j,-1} - (1 - \lambda f(\theta({x_j}^E))) l_{j,-1}\left[\alpha P_j l_j^{\alpha-1} + \beta \frac{\partial \mathbb{E}_j V_j^{init\prime}}{\partial l_j}\right] = 0, \tag{32}$$

$$\begin{aligned} &\lambda f'(\theta(x_j^E))\theta'(x_j^E) x_j^E l_{j,-1} + \lambda f(\theta(x_j^E)) l_{j,-1} \\ &-\lambda f'(\theta(x_j^E))\theta'(x_j^E) l_{j,-1}\left[\alpha P_j l_j^{\alpha-1} + \beta \frac{\partial \mathbb{E}_j V_j^{init\prime}}{\partial l_j}\right] = 0. \end{aligned} \tag{33}$$

There is no case in which firms hire and separate workers at the same time. Suppose $h_j > 0$. Combining (30), (31), (33), with $x_j^E \leq \kappa - c$, $\forall x_j^E$, the marginal value of x_j^E ($\frac{\partial V_j^{init}}{\partial x_j^E}$, the left-hand side of (33)) is strictly positive. Thus, $x_j^E = \kappa - c$ binds, which makes the marginal value of s_j ($\frac{\partial V_j^{init}}{\partial s_j}$,the left-hand side of 32) negative and firms never choose $s_j > 0$. Similarly, contracting firms ($s_j > 0$) will never choose $h_j > 0$ as (32) makes the marginal value of $h_j > 0$ ($\frac{\partial V_j^{init}}{\partial h_j}$, the left-hand side of (31)) negative with $\kappa > U$. This allows me to split it into the four cases for hiring, inactive (with or without quits), and contracting firms, and derive their decisions:

i) hiring firms: $x_j^E = \tilde{W}_j = \kappa - c$;

ii) inactive firms without quits: $x_j^E = \tilde{W}_j = \kappa - c$[57];

iii) inactive firms with quits: $\tilde{W}_j = \kappa - (\kappa - x_j^E)^{1+\gamma} c^{-\gamma}$ and x_j^E satisfies

$$\begin{aligned} &x_j^E + \frac{f(\theta(x_j^E))}{f'(\theta(x_j^E))\theta'(x_j^E)} \\ &-\left[\alpha P_j \Big((1 - \lambda f(\theta(x_j^E))) l_{j,-1}\Big)^{\alpha-1} + \beta \frac{\partial \mathbb{E}_j V_j^{init\prime}}{\partial l_j}\Big|_{l_j = (1-\lambda f(\theta(x_j^E)))l_{j,-1}}\right] = 0 \end{aligned} \tag{34}$$

iv) contracting firms: x_j^E, $\tilde{W}_j$, and s_j are determined by

$$\kappa - U = c\left[(1 + \theta(x_j^E)^\gamma)^{1+\frac{1}{\gamma}} - \lambda \theta(x_j^E)^{1+\gamma}\right] \tag{35}$$

$$\tilde{W}_j = \kappa - (\kappa - x_j^E)^{1+\gamma} c^{-\gamma}$$

$$\left[\alpha P_j l_j^{\alpha-1} + \beta \frac{\partial \mathbb{E}_j V_j^{init\prime}}{\partial l_j}\right] = \frac{U - \lambda x_j^E \Big(\theta(x_j^E)(1 + \theta(x_j^E)^\gamma)^{-\frac{1}{\gamma}}\Big)}{1 - \lambda \Big(\theta(x_j^E)(1 + \theta(x_j^E)^\gamma)^{-\frac{1}{\gamma}}\Big)}. \tag{36}$$

---

[57] Even without hiring, if P_j is high enough so that the marginal value of x_j^E ($\frac{\partial V_j^{init}}{\partial x_j^E}$, the left-hand side of (33)) is strictly positive, the optimal x_j^E is bound by the upper bound as in the hiring case, i.e. $x_j^E = \kappa - c$. This holds when $\kappa - c < \left[\alpha P_j l_j^{\alpha-1} + \beta \frac{\partial \mathbb{E}_j V_j^{init\prime}}{\partial l_j}|_{l = l_{j,-1}}\right]$, where firms stay inactive without any worker quits, i.e. $l_j = l_{j,-1}$.

Lastly, let's define $\hat{W}_j \equiv \Big(s_j U + (1-s_j)\big(\lambda f(\theta(x_j^E))x_j^E + \big(1-\lambda f(\theta(x_j^E))\big)\tilde{W}_j\big)\Big)$ as incumbent workers' value at the beginning of a period after observing the firm productivity P_j but before the firm's endogenous choices. $\hat{W}_j$ is determined and ranked by the following descending order: i) workers at hiring or inactive employers (no quit) have the highest $\hat{W}_j$, where $\hat{W}_j^{hire,noquit} = (\kappa - c)$; ii) workers at inactive employers (with quits) have the second-highest $\hat{W}_j$, where $\hat{W}_j^{quit} = \Big(\lambda f(\theta(x_j^E))x_j^E + \big(1-\lambda f(\theta(x_j^E))\big)\tilde{W}_j\Big)$; iii) workers at contracting employers (with lay-offs) or in the unemployment pool have the lowest $\hat{W}_j$, where $\hat{W}_j^{layoff} = \Big(s_j U + (1-s_j)\big(\lambda f(\theta(x_j^E))x_j^E + \big(1-\lambda f(\theta(x_j^E))\big)\tilde{W}_j\big)\Big)$ or $\hat{W}_j^{unemp} = U$.

First, $\big(\lambda f(\theta(x_j^E))x_j^E + \big(1-\lambda f(\theta(x_j^E))\big)\tilde{W}_j\big) \leq \hat{W}_j^{hire,noquit}$ holds as $x_j^E, \tilde{W}_j \leq \kappa - c$ for any active markets x_j^E and $\tilde{W}_j$. Using (29), it can be shown that $\hat{W}_j^{quit} = x_j^E - \theta(x_j^E)^\gamma(\kappa - x_j^E) + \lambda c\theta(x_j^E)^{1+\gamma}$, with x_j^E determined in (34). Also, the marginal value of s_j (the left-hand side of (32)) has to be weakly negative as this firm finds $s_j = 0$ to be optimal. This proves the following relationship $U \leq \Big(x_j^E + \frac{(1-\lambda f(\theta(x_j^E)))f(\theta(x_j^E))}{f'(\theta)\theta'(x_j^E)}\Big) = x_j^E - \big(1-\lambda f(\theta(x_j^E))\big)\theta(x_j^E)^\gamma(\kappa - x_j^E) \leq \hat{W}_j^{quit}$. Similarly, we can rephrase $\hat{W}_j^{layoff} = s_j U + (1-s_j)\Big(x_j^E - \theta(x_j^E)^\gamma(\kappa - x_j^E) + \lambda c\theta(x_j^E)^{1+\gamma}\Big)$, with x_j^E satisfying (35). With (35), $U = x_j^E - \theta(x_j^E)^\gamma(\kappa - x_j^E) + \lambda c\theta(x_j^E)^{1+\gamma}$, and $\hat{W}_j^{layoff} = \hat{W}_j^{unemp}$, $\forall s_j \in [0,1]$. It proves $\hat{W}_j^{unemp} = \hat{W}_j^{layoff} \leq \hat{W}_j^{quit} \leq \hat{W}_j^{hire,noquit}$.[58] $\square$

***Proof of Proposition 2*.** Following Proposition 1, along with the state contingency of contracts, workers' non-commitment and optimality condition (15), and the posteriors (4), given the worker's previous employment status, the wage is a function of firm state variables $(a_j, \tilde{P}_{j,-1}, l_{j,-1}, P_j)$. $\square$

***Proof of Proposition 3*.** Given (4) and the log normality assumption, there is a point $\hat{P}$ of $\ln P$, with which the cdf functions F for young and old firms follow $F^{old}(\ln P) \geq (\leq) F^{young}(\ln P)$ if $\ln P \geq (\leq)\hat{P}$, where $\hat{P} \equiv \frac{\bar{\nu}^{old}\sigma^{young} - \bar{\nu}^{young}\sigma^{old}}{\sigma^{young} - \sigma^{old}}$.[59] This implies young (old) firms' posterior distribution exhibits first-order stochastic dominance (FOSD) when $\ln P \geq (\leq)\hat{P}$.

[58]Furthermore, as $\frac{\partial(x_j^E - \theta(x_j^E)^\gamma(\kappa - x_j^E) + \lambda c\theta(x_j^E)^{1+\gamma})}{\partial x_j^E} \geq 0$ and (29), hiring, inactive firms provide the highest $\tilde{W}_j$, firms with worker quits provide the second-highest $\tilde{W}_j$, and firm with worker layoffs provide the lowest $\tilde{W}_j$ to their incumbent workers. Online Appendix C demonstrates that x_j^E increases with firm productivity P_j (and consequently $\tilde{W}_j$ and $\hat{W}_j$), even among firms with worker quits. This indicates that x_j^E (and thus $\tilde{W}_j$ and $\hat{W}_j$) is a weakly increasing function in firm productivity P_j.

[59]$\bar{\nu}^{young}$ ($\bar{\nu}^{old}$) and σ^{young} ($\bar{\nu}^{old}$) are the posterior mean and standard deviation for young (old) firms.

Let $\bar{\bar{\tilde{P}}}^H$ and $\bar{\bar{\tilde{P}}}^L$ be the thresholds of $\tilde{P}$ where $\hat{P} \geq \max[\mathcal{P}^q(a^{young}, \tilde{P}, l_{-1}),\ \mathcal{P}^q(a^{old}, \tilde{P}, l_{-1})]$ and $\hat{P} \leq \min[\mathcal{P}^l(a^{young}, \tilde{P}, l_{-1}), \mathcal{P}^l(a^{old}, \tilde{P}, l_{-1})]$, respectively, given $a^{young} < a^{old}$ and l_{-1}.[60] Suppose $\tilde{P} \geq \bar{\bar{\tilde{P}}}^H$. Then, $\hat{P} \geq \max[\mathcal{P}^q(a^{young}, \tilde{P}, l_{-1}), \mathcal{P}^q(a^{old}, \tilde{P}, l_{-1})]$ holds for any $\tilde{P} \geq \bar{\bar{\tilde{P}}}^H$ as $\hat{P}$ is increasing in $\tilde{P}$. Next, the following can be derived: $\int_{\hat{P}} \hat{W}^{old} dF^{old}(\ln P) = \int_{\hat{P}} \hat{W}^{young} dF^{young}(\ln P) = \hat{W}^{hire,noquit}(1 - F_z(\bar{\nu}^{old} - \bar{\nu}^{young}))$, where $F_z(\cdot)$ is the standardized normal cdf, and $\hat{W}^{hire,noquit} = \kappa - c$ is constant across firms.[61] As $\hat{W}_j$ is weakly increasing in P_j, the FOSD of F^{old} implies $\int^{\hat{P}} \hat{W}^{old} dF^{old}(\ln P) \geq \int^{\hat{P}} \hat{W}^{old} dF^{young}(\ln P) \geq \int^{\hat{P}} \hat{W}^{young} dF^{young}(\ln P)$. This derives the following relationship: $\int \hat{W}^{old} dF^{old}(\ln P) \geq \int \hat{W}^{young} dF^{young}(\ln P)$. Similarly, if $\tilde{P} \leq \bar{\bar{\tilde{P}}}^L$, $\int^{\hat{P}} \hat{W}^{young} dF^{young}(\ln P) = \int^{\hat{P}} \hat{W}^{old} dF^{old}(\ln P) = \hat{W}^{layoff} F_z(\bar{\nu}^{old} - \bar{\nu}^{young})$ holds, as $\hat{P} \leq \min[\mathcal{P}^l(a^{young}, \tilde{P}, l_{-1}), \mathcal{P}^l(a^{old}, \tilde{P}, l_{-1})]$, and $\hat{W}^{layoff}$, derived from (33) and (36), is also constant across firms. Given the FOSD of F^{young}, the following relationship holds: $\int_{\hat{P}} \hat{W}^{young} dF^{young}(\ln P) \geq \int_{\hat{P}} \hat{W}^{young} dF^{old}(\ln P) \geq \int_{\hat{P}} \hat{W}^{old} dF^{old}(\ln P)$. Thus, $\int \hat{W}^{old} dF^{old}(\ln P) \leq \int \hat{W}^{young} dF^{young}(\ln P)$ is proved. Linking these results to Proposition 1 completes the proof for wages. $\square$

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[60] The productivity cutoffs depend on $(a_j, \tilde{P}_{j,-1}, l_{j,-1})$. As shown in Online Appendix C, given all else equal, these cutoffs are lower for older firms if firms are high-performing (i.e., sufficiently high $\tilde{P}_{j,-1}$), and lower for younger firms if firms are low-performing (i.e., sufficiently low $\tilde{P}_{j,-1}$). Also, all else equal, they decrease with $\tilde{P}_{j,-1}$.

[61] Note that $F^{old}(\hat{P}) = F^{young}(\hat{P}) = F_z(\bar{\nu}^{old} - \bar{\nu}^{young})$.

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Supplementary Materials The Online Appendix contains supplementary materials.

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