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Pennsylvania State University and IZA

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IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Workers' Job Prospects and Young Firm Dynamics*

This paper investigates how worker beliefs and job prospects impact the wages and growth of young firms, as well as the aggregate economy. Building a heterogeneous-firm directed search model where workers gradually learn about firm types, I find that learning generates endogenous wage differentials for young firms. High-performing young firms must pay higher wages than equally high-performing old firms, while low-performing young firms offer lower wages than equally low-performing old firms. Reduced uncertainty or labor market frictions lower the wage differentials, thereby enhancing young firm dynamics and aggregate productivity. The results are consistent with U.S. administrative employee-employermatched data.

JEL Classification: E20, E24, J31, J41, J64, L25, L26, M13, M52, M55

Keywords: wage differentials, firm dynamics, learning, search frictions, uncertainty

Corresponding author:
Seula Kim
Department of Economics
Pennsylvania State University
614 Kern Building
University Park, PA 16802
USA
E-mail: seulakim@psu.edu

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Acquiring workers is essential for firms to grow, especially for young firms with high growth potential. High-growth young firms account for a disproportionate share of gross job creation and productivity growth in the U.S.[1] However, young firms are nascent and have short track records. When workers decide to take a job, they consider the job prospects by assessing the expected stream of wages, layoff possibilities, and potential future career development, based on their beliefs about firm fundamentals.

Given limited history, workers are less certain about young firm performance as an indicator of their actual fundamentals. This increases workers' uncertainty about young firms, shaping their incentives to join these firms differently. Workers' job prospects and incentives can be important to understanding young firm dynamics, yet this mechanism has been less studied.

How do workers' job prospects impact the wage and growth of young firms? What are the aggregate implications of this channel? My paper investigates these questions both theoretically and empirically. On the side of theory, I construct a heterogeneous firm directed search model with learning about firm types to provide a mechanism through which workers' job prospects affect the wage and growth of firms, as well as aggregate outcomes. Empirically, I test the model with two comprehensive databases from the U.S. Census Bureau; the Longitudinal Business Database (LBD) and the Longitudinal Employer-Household Dynamics (LEHD).

First, theoretically, I extend the directed search model of Schaal (2017) by introducing learning as in Jovanovic (1982). A novel feature of the model is that workers need to learn about firms' underlying productivity types along the firm life cycle,

[1]Using the Business Dynamics Statistics, I find that young firms (aged five or less) accounted for 29.69% of job creation in the U.S. from 1998 to 2014, despite representing only 12.60% of total employment. Notably, high-growth young firms (those with the DHS employment growth above 0.8, i.e., $\frac{(Emp_{it}-Emp_{it-1})}{0.5(Emp_{it}+Emp_{it-1})} > 0.8$), are only 3.36% of total employment, but contribute significantly to job creation, representing 21.22%. See also Haltiwanger (2012), Haltiwanger et al. (2013), Decker et al. (2014), Decker et al. (2016), and Foster et al. (2018).

and take jobs based on their beliefs about firm types. In the model, workers' learning and uncertain job prospects create endogenous wage differentials for young firms relative to otherwise similar mature firms.

Specifically, I find that young firms with high demonstrated potential, defined as those with high average performance over past periods, 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. At the same time, young firms with low demonstrated potential, those with low past-average performance, can pay wage discounts compared to their otherwise similar mature counterparts. This follows the same logic, where the low-performing young firms benefit from the fact that their limited history gives them some upside risk. This is one of the novel predictions of this model.

The model quantifies the macroeconomic impact of the job prospects channel on young firm activity and aggregate productivity. Counterfactual analysis shows that reducing fundamental uncertainty about young firms' job prospects (e.g., lower noise-to-signal ratio in learning) or lowering labor search frictions can enhance firm entry, increase the share and growth of high-growth young firms, and boost aggregate productivity. Reduced uncertainty accelerates learning about firm types and narrows the gaps in workers' job prospects between young and mature firms. Lower search frictions ease workers' concerns about future prospects at a firm with greater labor mobility. These all reduce wage differentials for young firms. Thus, under lower uncertainty or search frictions, high-performing firms grow faster with lower wage premia, while low-performing firms grow less or exit more with reduced wage discounts. This leads to the increase in aggregate productivity.

Next, I use the Census datasets and confirm these model predictions. In particular, I merge the LBD with LEHD, where the LBD tracks the universe of U.S. non-farm businesses and establishments, and the LEHD tracks the earnings, jobs, and demographics of workers reported in the U.S. Unemployment Insurance (UI) systems. Using the linked data, I estimate an individual-level earnings regression informed by the model. I find that, after controlling for worker heterogeneity and observable firm characteristics, i) young firms with high past-average productivity pay more than their observationally similar mature counterparts, while ii) those with low past-average productivity pay less compared to their otherwise similar mature counterparts. I also find that these earnings differentials are negatively associated with firm hiring and employment growth.

Moreover, I estimate the impact of uncertainty on the earnings differentials of young firms by using industry-level variation in the noise-to-signal ratio, constructed from the dispersion of firm-level productivity shocks and fixed effects. I find that earnings differentials are more (less) pronounced in industries with higher (lower) uncertainty. Lastly, I find that higher uncertainty has negative impacts on industry-level firm entry, young firm activities, productivity, which supports 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 identifying workers' job prospects as a novel source affecting firm entry and young firm growth.

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 potential, 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 earnings differentials and firm performance.

Lastly, 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.[2] Furthermore, the model retains block recursivity, ensuring tractability without sacrificing richness. This feature allows for quantifying the aggregate

[2]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.

implications of the learning and search frictions and the resulting wage differentials for young firms in a tractable manner.

The remainder of this paper is structured as follows: Section 1 develops a heterogeneous firm directed search model with a firm-type learning process; Section 2 lays out the model's main implications and mechanisms; Section 3 describes the model calibration and counterfactual exercises; Section 4 uses the data and tests the model implications; and Section 5 concludes.

1 Theoretical Model

The baseline model builds on Schaal (2017) by introducing a firm-type learning process as in Jovanovic (1982). The model consists of heterogeneous firms with homogeneous workers with symmetric information and frictional labor markets. Both firms and workers are risk neutral with the same discount rate β. Firms all produce homogeneous goods.

1.1 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}.[3]

Both entrants and workers start with a prior $\nu_j \sim N(\bar{\nu}_0, \sigma_0^2)$ at firm birth. After

[3]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 ($\frac{\sigma_\varepsilon}{\sigma_0}$).

observing P_{jt}, they update their beliefs using Bayes' rule as follows:

$$\nu_j|_{P_{jt}} \sim N(\bar{\nu}_{jt}, \sigma^2_{jt}),$$

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

a_{jt} is the age of firm j at period t, $\bar{\nu}_{jt}$ and σ^2_{jt} denote the updated posterior mean and variance about firm j's type at the end of period t (or at the beginning of $t+1$), respectively, and $\tilde{P}_{jt} \equiv \frac{\left(\sum_{i=0}^{a_{jt}} \ln P_{jt-i}\right)}{a_{jt+1}}$ is the average of log productivity over past periods up to time 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.[4] Figure 1 illustrates the posterior beliefs across different firm ages, for a given level of past-average productivity.[5]

1.2 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 value x_{jt} that firms (j) promise to workers in contracts.[6] Firms and workers choose a submarket to search in by considering a

[4]See Appendix B for more details and properties of the Bayes' rule.

[5]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.

[6]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.

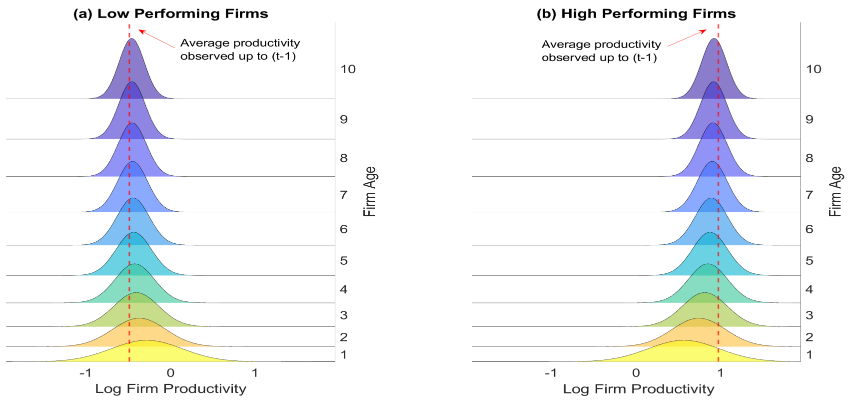

Figure 1: Posterior Distribution of Firm Type

Note: This figure illustrates the posterior distribution of firm types over the firm life cycle. The left panel depicts equally low-performing firms ($\tilde{P}_{jt-1} < \bar{\nu}_0$), and the right panel shows equally high-performing firms ($\tilde{P}_{jt-1} > \bar{\nu}_0$) of different ages.

trade-off between the promised utility of a given contract and the corresponding matching probability. Matches are created using a CES matching function with elasticity parameter γ. 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.[7] 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:

$$\mathbf{\Omega^i_{jt}} = \{w^i_{jt}, d^i_{jt+1}, s^i_{jt+1}, \tilde{W}^i_{jt+1}\}, \tag{2}$$

where the last three terms are contingent on the firm's next period state variables

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.

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

$(a_{jt+1}, \tilde{P}_{jt}, P_{jt+1}, l_{jt})$ with firm employment size l_{jt} at the end of period t. Firms offer common contracts across workers with the same employment status (ex-post heterogeneity), which makes them offer the same state-contingent next-period variables to workers.[8,9] 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.[10]

1.3 The Problems of Workers and Firms

Unemployed workers. Unemployed workers' value function U follows:

$$U = b + \beta \mathbb{E}\Big[\max_{x^{U\prime}} (1 - f(\theta(x^{U\prime})))U' + f(\theta(x^{U\prime}))x^{U\prime}\Big], \tag{3}$$

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 workers i at firm j have the following value function

[8] 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 $t+1$.

[9] The only source of worker heterogeneity is their employment status (either unemployed or employed, and if employed, where they are employed). There is neither worker ex-ante heterogeneity nor human capital accumulation. Thus, firms offer the same state-contingent variables to workers (either hired at t or remaining incumbents from t) as the workers get the same status at the beginning of $t+1$ once joining the firm at t. The current wage at t can vary across them, depending on where they came from $t-1$.

[10] 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 $t-1$.

W_j^i after the search and matching process.[11,12]

$$W^i(a_j, \tilde{P}_{j,-1}, l_{j,-1}, P_j, \mathbf{\Omega_j^i}) = w_j^i + \beta \mathbb{E}_j \Bigg[\Big(\delta + \big(1-\delta\big)\big(d_j' + (1-d_j')s_j'\big) \Big) U'$$

$$+(1-\delta)(1-d_j')(1-s_j') \max_{x_j^{E'}} \Big(\lambda f(\theta(x_j^{E'}))x_j^{E'} + \big(1-\lambda f(\theta(x_j^{E'}))\big)\tilde{W}_j' \Big) \Bigg]. \quad (4)$$

This shows that the workers first receive the wage w_j^i as specified in their contracts. For the following period, they consider three possible cases: (i) they are dismissed, either because the 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'.[13] $\mathbb{E}_j(\cdot)$ 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:

$$J(a_j, \tilde{P}_{j,-1}, l_{j,-1}, P_j, \{\mathbf{\Omega^i_{j,-1}}\}_{i\in[0,l_{j,-1}]}) = \max_{\substack{\{\mathbf{\Omega^i_j}\}_{i\in[0,l_j]},\\ h_j, x_j}} P_j l_j^\alpha - \textstyle\int_0^{l_j} w_j^i di - c_f$$

$$-\tfrac{c}{q(\theta(x_j))} h_j + \beta(1-\delta)\mathbb{E}_j \Bigg[(1-d_j') J(a_j', \tilde{P}_j, l_j, P_j', \{\mathbf{\Omega^i_j}\}_{i\in[0,l_j]}) \Bigg] \quad (5)$$

at the search and matching stage, subject to:

$$l_j = h_j + (1-s_j)\big(1 - \lambda f\big(\theta(x_j^E)\big)\big) l_{j,-1} \quad (6)$$

[11] 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).

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

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

$$\lambda f(\theta(x_j^{E\prime}))x_j^{E\prime} + (1 - \lambda f(\theta(x_j^{E\prime})))\tilde{W}_j' \geq U' \tag{7}$$

$$x_j^{E\prime} = \text{argmax}_x\, f(\theta(x))\big(x - \tilde{W}_j'\big) \tag{8}$$

$$W(a_j, \tilde{P}_{j,-1}, l_{j,-1}, P_j, \mathbf{\Omega_j^i}) \geq x_j \quad \text{for new hires } i \in [0, h_j] \tag{9}$$

$$W(a_j, \tilde{P}_{j,-1}, l_{j,-1}, P_j, \mathbf{\Omega_j^i}) \geq \tilde{W}_j \quad \text{for incumbent workers } i \in [h_j, l_j], \tag{10}$$

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 $\mathbf{\Omega_j^i}$, 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, each of which is a function of market tightness $\theta(x_j)$.

(6) is the employment law of motion, (7) is a participation constraint, which prevents workers' return to unemployment unless separations take place, and (8) 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.[14] (9) and (10) are promise-keeping constraints for new hires and surviving incumbent workers, respectively.[15]

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

[14] 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 $\tilde{W}_j'$. This is key to the unique determination of wages. 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.

[15] Because of the commitment assumption, the firm needs to announce contracts that deliver at least x_j and $\tilde{W}_j$ to their newly hired and incumbent workers, respectively.

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:

$$\int \max_{\substack{\mathbf{\Omega_j^{ie}}=\{w_j^{ie},d_j',s_j',\tilde{W}_j'\},\\ d_j^e,l_j^e,x_j^e}} (1-d_j^e)\Bigg(P_j(l_j^e)^\alpha - w_j^{ie}l_j^e - c_f - \frac{c}{q(\theta(x_j^e))}l_j^e \tag{11}$$

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

where $\mathbf{\Omega_j^{ie}}$ is entrant j's contract to worker i, which consists of the four components in (2). 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.[16] 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 (7) and (8) for retaining incumbent workers in the next period, and the promise-keeping constraint (12) for new hires in the current period. Figure 2 outlines the model timeline.

$$W(0,0,0,P_j,\mathbf{\Omega_j^{ie}}) \geq x_j^e \quad \text{for all workers } i \in [0, l_j^e]. \tag{12}$$

[16]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.

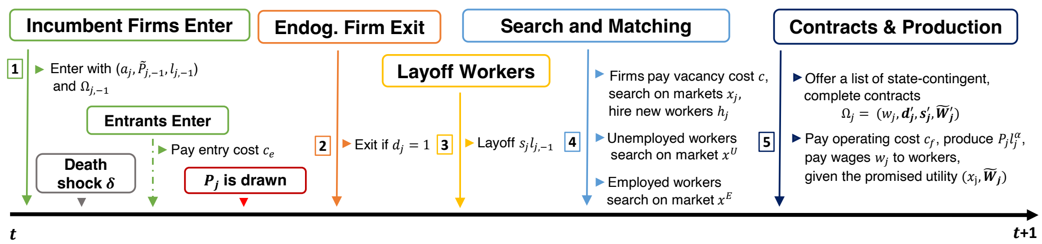

Figure 2: Timeline of the model

1.4 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

$$x^U = \operatorname*{argmax}_x f(\theta(x))(x - U), \tag{13}$$

with the outside option U given by (3). Employed workers at firm j solve

$$x^E(a_j, \tilde{P}_{j,-1}, l_{j,-1}, P_j) = \operatorname*{argmax}_x f(\theta(x))(x - \tilde{W}(a_j, \tilde{P}_{j,-1}, l_{j,-1}, P_j)), \tag{14}$$

taking into account their outside option $\tilde{W}_j$ provided by the current employer j. Equations (13) and (14) determine workers' optimal labor submarkets, where workers consider the trade-off between the value of a give contract (or unemployment) and the corresponding probability of being matched.[17]

On firms' side, (5) and (11) imply that all firms face the following same problem

[17] 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).

when choosing their optimal submarket x_j:

$$x_j = \underset{x}{\operatorname{argmin}} \frac{c}{q(\theta(x))} + x, \tag{15}$$

independent of their state variables. This means that all firms are indifferent across the various submarkets x_j that are solutions to (15).

Labor market equilibrium is pinned down by the (possibly multiple) intersections between the decisions of workers and firms (13), (14), and (15).[18]

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 employment size l_{-1} at the beginning of each period. This distribution satisfies the following law of motion for $a \geq 1$:

$$\begin{aligned} G(a+1, \tilde{P}, l) = (1-\delta) \int_{l_{-1}} \int_{\tilde{P}_{-1}} \Bigg\{ &\Big(1 - d\big(a, \tilde{P}_{-1}, l_{-1}, e^{(a+1)\tilde{P} - a\tilde{P}_{-1}}\big)\Big) \\ \times \mathbb{I}\big(l(a, \tilde{P}_{-1}, l_{-1}, e^{(a+1)\tilde{P} - a\tilde{P}_{-1}}) = l\big) G(a, \tilde{P}_{-1}, l_{-1}) f_P(e^{(a+1)\tilde{P} - a\tilde{P}_{-1}}) &\Bigg\} d\tilde{P}_{-1} dl_{-1}, \\ \text{where } G(1, \tilde{P}_{-1}, l_{-1}) = M^e(1 - d^e(\mathrm{e}^{\tilde{P}_{-1}})) \mathbb{I}\big(l^e(\mathrm{e}^{\tilde{P}_{-1}}) = l_{-1}\big) f_P(\mathrm{e}^{\tilde{P}_{-1}}). \end{aligned}$$

$\mathbb{I}(\cdot)$ 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 (11).[19][20,21]

[18]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.

[19]$f_P(P) = \int_\nu f(P|\nu) f_\nu(\nu) d\nu$, where $f_\nu(\cdot)$ is the pdf of ν, with $\nu \sim N(\bar{\nu}_0, \sigma_0^2)$, and $f(P|\nu)$ is the conditional pdf of P given ν, with $\ln P \sim N(\nu, \sigma_\varepsilon^2)$.

[20]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 $l(a, \tilde{P}_{-1}, l_{-1}, e^{(a+1)\tilde{P} - a\tilde{P}_{-1}}) = l$.

[21]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 $l^e(\mathrm{e}^{\tilde{P}_{-1}}) = l_{-1}$.

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

$$\sum_{a\geq 1}\int_{\tilde{P}_{-1}}\int_{l_{-1}}\int_{P}\Bigg\{\Big(\delta+(1-\delta)\big(d(a,\tilde{P}_{-1},l_{-1},P) \tag{16}$$

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

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

where the inflow to the unemployment pool equals the outflow from it.[22]

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* $\big\{\big(\mathbf{\Omega_j^{ie}}=\{w_j^{ie},d_j',s_j',\tilde{W}_j'\}\big)_{i\in[0,l_j^e],},d_j^e,l_j^e,x_j^e\big\}_j$*; (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 mass of entrants* M^e*; such that equations* (1),(3)-(5)*,* (11)*,* (13)-(16) *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* $N=1$*.*

2 Model Implications

This section presents main implications of the model.

Lemma 1. *Firm promise-keeping constraints* (9) *and* (10) *bind.*

[22] The left-hand side of (16) 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.

Proof: From (4)*,* (5)*,* (9)*, and* (10)*, each firm j optimally chooses the lowest possible $\{w_j^i\}_i$ that complies with the promise-keeping constraints.*

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 Appendix A.*

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 Appendix A.*

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 (14), the firm's choice of $\tilde{W}$ depends on its desire to retain workers in the face of potential poaching by other firms.[23] Thus, expanding firms with more willingness to retain workers offer higher values to deter poaching than contracting firms.[24] Also, following (7), workers' value in unemployment is lower than the value of being employed.

Then workers expect higher future value at firms that are more likely to hire or retain workers in the next period, which guarantees higher stability as well as better career trajectories to workers. This is because these firms would not only offer higher continuation value to workers but also make workers more ambitious when targeting their on-the-job search options. On the other hand, if firms are expected to lose workers in the next period, either by poaching or layoffs, workers anticipate lower future value, as these are seen as less stable and less willing to retain workers with

[23]In Appendix A (in equation (A.4)), I prove 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.

[24]This is due to the vacancy cost as it is more costly to lose incumbents and hire new workers.

strong continuation utility. Therefore, workers' future expected value is higher for firms with better posteriors and more (less) likelihood of keeping (losing) workers.

Next, I discuss how the equilibrium wage depends on firm age.

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 Appendix A.

This shows that wage differentials exist between young firms and otherwise similar mature firms as workers perceive them differently due to learning.

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 (with the same employment status) 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.*[25] *Proof: See Appendix A.*

In other words, to a given type of workers, younger firms with high past-average productivity $\tilde{P}_{-1}$ pay wage premia relative to observationally similar mature counterparts with the same $(\tilde{P}_{-1}, l_{-1}, P)$. Conversely, young firms with low past-average productivity $\tilde{P}_{-1}$ pay wage discounts relative to seemingly identical mature counterparts.[26]

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.[27] If two firms exhibit equally good (bad) performance

[25] 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 priors $\bar{\nu}_0$.

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

[27] This relates to the posterior mean in (1), which is a weighted sum of past-average average

but differ in age, the posterior beliefs and expected future value for workers at the younger firm are relatively worse (better) than at the mature counterpart. This results in wage premia (discounts) for young firms compared to otherwise similar mature firms, all else equal.

Figure 3 displays workers' expected future value (top) and the equilibrium wages for unemployed workers (middle) and incumbent workers (bottom) at high-performing firms (left) and low-performing firms (right) across different ages, controlling for workers' previous employment status and other firm characteristics (equally sized firms with equal past-average and current productivity).[28,29] This shows wage premia for high-performing young firms relative to equally high-performing mature firms and discounts for low-performing young firms relative to equally low-performing mature firms.

3 Quantitative Analysis

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

I internally calibrate the remaining parameters $\{b, \lambda, \gamma, c, c_e, \delta, \bar{\nu}_0, \sigma_0, \sigma\varepsilon, c_f\}$ to jointly match the following target moments: (i) the employment-unemployment (EU) rate, (ii) the employment-employment (EE) rate, (iii) the unemployment-employment (UE) rate, (iv) the hiring rate, (v) the firm entry rate, (vi) the share of

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.

[28] These figures are calculated using the calibration described in the next section.

[29] The equilibrium wages to poach workers from a given source follow the same pattern.

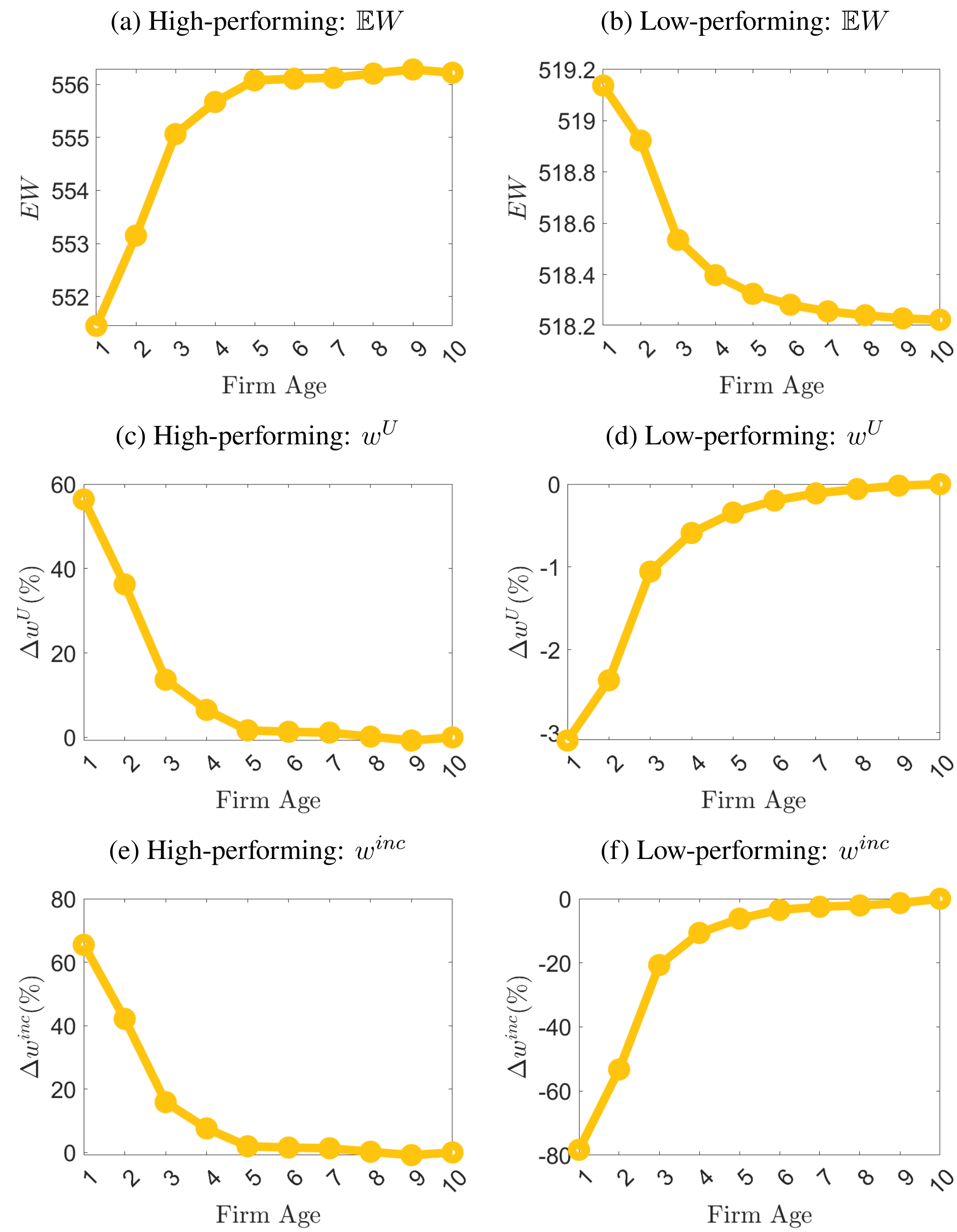

Figure 3: High vs. Low-performing Firms

Note: This figure shows workers' expected future value (top), wages for unemployed workers (middle), and incumbent workers (bottom) for high-performing firms (left) and low-performing firms (right) with the same $(\tilde{P}_{j,-1}, P_j, l_{j,-1})$ across different ages. Wage differentials are presented as percentage differences relative to those paid by the oldest firm (age 10).

Table 1: Calibration

	Description	Value		Description	Value
β	Discount factor	0.99	c_e	Entry cost	28.30
α	Revenue curvature	0.65	δ	Death shock	0.01
N	Worker mass	1.00	$\bar{\nu}_0$	Initial prior mean	1.27
b	Leisure value	0.42	σ_0	Initial prior SD	0.72
λ	OTJ search effic.	0.70	σ_ε	Shock SD	0.65
γ	CES parameter	0.40	c_f	Operating cost	2.78
c	Vacancy cost	2.12			

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

Table 2: Target Moments

Moment	Data	Model	Moment	Data	Model
UE rate (%)	24.4	24.7	Young firm share (%)	32.1	27.8
EE rate (%)	3.4	3.3	Mean $\ln P$ ratio ($\frac{age0}{age16}$)	0.96	0.95
EU rate (%)	5.4	5.0	SD $\ln P$ (age0)	0.79	0.78
Hiring rate (%)	3.6	4.8	Mean $\ln P$ ratio ($\frac{age5}{age16}$)	0.99	0.98
Firm entry (%)	7.9	7.9	SD $\ln P$ (age5)	0.76	0.76

Note: The table lists the target moments used to calibrate the model. The data sources are the U.S. Bureau of Labor Statistics (2001-2014a), U.S. Bureau of Labor Statistics (1998-2014b), U.S. Census Bureau (1998-2014a) and U.S. Census Bureau (2000-2014b), as well as Haltiwanger et al. (2016).

young firms, (vii)-(viii) the mean firm productivity at ages 0 and 5 (relative to age 16), and (ix)-(x) the standard deviation of firm productivity at ages 0 and 5.[30] I apply the simulated method of moments (SMM) that minimizes the sum of squared percentage distances between the model-simulated moments and their counterpart moments in data.

[30]The UE rate is the share of unemployed workers who find a job in the next period, the EE rate is the share of employed workers who move to a new job without any nonemployment spell, and the EU rate is the share of employed workers who switch to nonemployment status. The share of young firms is the share of firms aged five year or less in total firms. The mean firm productivity is the relative average (log) labor productivity of firms at age 0 (or 5) to age 16 within industries, and the standard deviation reflects the within-industry dispersion of (log) labor productivity by firm age.

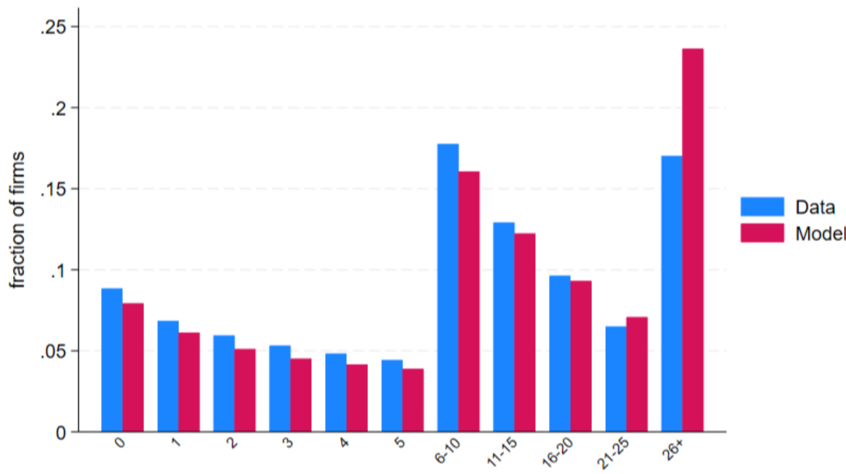

Figure 4: Firm Age Distribution: Data vs. Model

Note: This graph compares the firm age distribution in the model with the data (BDS 1991–2014). The blue bars indicate the data moments, and the red bars present their counterparts in the model.

The calibration results are presented in Table 2, where the model performs well in matching the target moments overall. In addition, the calibrated model aligns well with firm age distribution in the data, which is untargeted. This is presented in Figure 4.

The following discusses the most relevant moment for each parameter: b and λ are calibrated to match the EU and EE rates, respectively, as measured in U.S. Census Bureau (2000-2014b) J2J data.[31] γ and c are jointly calibrated to target quarterly UE and hiring rates in U.S. Bureau of Labor Statistics (1998-2014b). c_e and δ are calibrated to the firm entry rate and the share of young firms calculated in U.S. Census Bureau (1998-2014a) Business Dynamics Statistics, respectively. Lastly, $\bar{\nu}_0$ and σ_0 calibrated to match the relative mean and standard deviation of

[31]To be consistent with the model, only hires with no observed interim nonemployment spell (within-quarter job-to-job transitions) are used to define the EE rate. This is the rate of "EEHire" from main jobs in the J2J database. The EU rate is computed by the variable "ENPersist" in the J2J database. The J2J data begins in 2000Q2, and the average between 2000Q2 and 2014Q4 is used.

Table 3: Counterfactual Exercises

Description	Baseline	$\frac{\sigma_\varepsilon}{\sigma_0} \downarrow$	$c \downarrow$
Firm entry rate (%)	7.9	9.6	10.7
Share of young firms (%)	27.8	32.1	35.2
Share of high-growth young firms (%)	4.65	5.43	8.67
Employment share of high-growth young firms (%)	4.17	4.57	9.20
Aggregate productivity	2.42	2.69	2.59
p90 firm productivity	3.40	3.56	3.54

Note: This table presents counterfactual results comparing scenarios of lower uncertainty (in the second column) and lower search frictions (in the third column).

Table 4: Wage Differentials for Young Firms

	Baseline	$\frac{\sigma_\varepsilon}{\sigma_0} \downarrow$	$c \downarrow$
Young	-0.677***	-0.352***	-0.045***
	(0.027)	(0.043)	(0.002)
Young × High performing	1.031***	0.366***	0.052***
	(0.036)	(0.046)	(0.002)

Note: The table reports the wage regression results using the simulated model. The dependent variable is the wages of unemployed 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 above the cross-sectional mean at a given time. Controls for past average productivity, current productivity, and log employment size of firms are included. Observations are unweighted. The first column presents the baseline economy, while the second and third columns show the counterfactual cases with lower uncertainty and lower search costs, respectively.

(log) productivity for startups, while σ_ε and c_f are calibrated to match those of age 5 firms. These moments are sourced from Haltiwanger et al. (2016).[32,33]

Using the calibrated model, I conduct two counterfactual exercises to examine the aggregate implications of this channel: i) reducing uncertainty by lowering noise-to-signal ratio, $\frac{\sigma_\varepsilon}{\sigma_0}$, to 0.72; and ii) lowering search frictions by setting c to 0.1.[34]

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

[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 data at the same frequency as the data counterparts.

[34]In order to change the noise-to-signal ratio, I set σ_ε to 0.56 (with the within-industry standard

Table 3 presents the results for both cases.

First, both reduced uncertainty and search frictions promote firm entry and young firm activity. Specifically, the (employment) share of high-growth young firms increases in both counterfactual economies.[35] Second, the firm-level productivity distribution shifts to the right, with more productive firms performing better in both counterfactuals. This is reflected in the increase in aggregate productivity and the higher productivity level at the top decile.

The underlying intuition is straightforward: both factors reduce wage differentials for young firms. First, as uncertainty decreases, the speed of learning about firm types slows. As a result, the gap in job prospects between young and mature firms narrows, which reduces the wage premia for high-performing young firms and the wage discounts for low-performing ones. Second, as search frictions decrease, workers gain more flexibility to move across firms, making them less concerned about future prospects, even if they have limited information about young firms. This, in turn, reduces wage differentials across firms of different ages.[36,37]

Table 4 presents the results of wage regressions on the dummies for young firms and high-performing young firms using simulated data from the model, supporting this explanation.[38] With reduced wage differentials, high-performing young firms can survive and grow more effectively, while low-performing young firms are more

deviation of σ_ε estimated around 0.1 in the data) and adjust σ_0 accordingly to hold the variance of log productivity ($\sqrt{\sigma_0^2 + \sigma_\varepsilon^2}$) constant. This ensures that only the uncertainty changes, without affecting the mean level of productivity under the log-normal distribution.

[35] High-growth firms are defined by the top decile of the cross-sectional firm-level employment growth distribution. When comparing high-growth young firms across these economies, I use the same top decile cutoff for high-growth firms as in the baseline economy to ensure a consistent comparison of the same set of entities.

[36] Note that in an extreme case with either no information or no search frictions, these wage differentials across firm age would become zero.

[37] Appendix E show them in a graph.

[38] As baseline, I use wages paid to hire unemployed workers. A similar regression with wages to poach or retain workers (controlling for their previous employment status) gives consistent results. Due to space limitations, I only show the main coefficients.

likely to exit compared to the baseline economy. This enhances selection and increases the value of firm entry.

The results suggest important policy implications. Reducing uncertainty through better information on firm performance (e.g., platforms that publicly share key performance indicators or VC/consulting programs offering performance feedback) could accelerate learning about firm types.[39] This can help reduce learning frictions about young firms and improve selection with high-performing young firms growing and low-performing ones exiting more quickly, thereby boosting economic efficiency. Additionally, lowering search frictions, such as through job matching platforms or job search assistance, would allow workers to find a job easily and improve labor allocation.[40] This can help reduce wage gaps and foster young firm growth.

4 Empirical Analysis

Data. To test the model, I construct a comprehensive dataset of employee-employer matched records with firm and worker characteristics, linking Longitudinal Business Database (LBD) and Longitudinal Employer Household Dynamics (LEHD) in U.S. Census Bureau (1998-2014c), from 1998 to 2014.

The LBD tracks the universe of U.S. establishments and firms annually from 1976, and the LEHD collects quarterly employment and demographic information

[39]In VC or consulting programs, firms can submit key performance metrics such as revenue, employment growth, customer acquisition, and employee compensation. Consultants or VCs could compare these metrics to industry standards, helping firms recognize their potential and growth trajectory. By disclosing these key performance indicators to workers, it reduces information frictions on the workers' side.

[40]The government could assist job search by subsidizing training programs, career counseling, and job search resources for workers. The availability of remote work and flexible job arrangements could also help reduce search frictions. Additionally, a social norm against job hopping, which exists in some countries or industries, might be another source of search frictions. Removing such social norms can also reduce search frictions and enhance job mobility.

of workers from the Unemployment Insurance (UI) system. My data covers 60% of U.S. private sector employment with access to 29 states.[41]

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 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).[42] 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.[43] I link the LEHD to the LBD and identify employers associated with each job held by workers. Further data details are provided in Appendix F.

Learning Process. The firm-type learning process is estimated as follows:

$$\ln P_{jt} = \rho \ln P_{jt-1} + \nu_j + \varepsilon_{jt}. \tag{17}$$

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.[44] 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

[41]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.

[42]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.

[43]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.

[44]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 the model. The remaining terms are denoted by $\ln \hat{P}_{jt} \equiv \hat{\nu}_j + \hat{\varepsilon}_{jt}$, which I use to map into the model productivity.[45]

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.[46] I use $\ln \hat{P}_{jt}$ and $\tilde{P}_{jt-1}$ in my regression below as measures representing the current and past-average productivity levels, respectively.

I define high-performing firms as those with average productivity above the industry mean of estimated prior mean as follows:

$$\mathbb{I}_{jt}^{H} \equiv \begin{cases} 1 & \text{if} \quad \tilde{P}_{jt-1} > \frac{\sum_{j \in g(j,t)} \hat{\nu}_j}{N_{g(j,t)}} \\ 0 & \text{otherwise,} \end{cases}$$

where $N_{g(j,t)}$ is the number of firms in industry $g(j,t)$ and year t.[47]

Uncertainty. I construct the industry-level uncertainty as follows:

$$Uncertainty_{gt} \equiv \frac{\hat{\sigma}_{\varepsilon gt}}{\hat{\sigma}_{0gt}}, \tag{18}$$

where $\hat{\sigma}_{\varepsilon gt}$ and $\hat{\sigma}_{0gt}$ are the cross-sectional dispersion of $\hat{\varepsilon}_{jt}$ and $\hat{\nu}_j$ estimated in (17)

[45]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}.

[46]This is the main sample with summary statistics shown in Appendix F.3.

[47]This is based on the numerical findings of the model. As a robustness check, I also use different thresholds to define high-performing firms, such as the within-industry cross-sectional median or the 75th percentiles or the within-industry-cohort mean of the estimated prior mean productivity. The results are robust and available upon request.

for each industry g. This is known as the "noise-to-signal" ratio.[48]

4.1 Earnings Differentials and Firm Outcomes

To test the job prospects channel, I use two-stage earnings regressions. In the first stage, I take out the effect of worker heterogeneity in worker earnings as follows:

$$y_{it} = \delta_i + \eta_t + X_{it}\gamma + \epsilon_{it}, \tag{19}$$

where y_{it} is the log Q1 earnings of worker i in year t, δ_i is a worker effect, η_t is a year effect, and X_{it} is a vector of controls for individual age, using quadratic and cubic polynomials centered around age 40.[49,50,51] Next, I run the following regression with the earnings residuals $\hat{\epsilon}_{it}$ in (19):

$$\begin{aligned}\hat{\epsilon}_{it} = & \beta_1 Young_{j(i,t)t} + \beta_2 Young_{j(i,t)t} \times \mathbb{I}^H_{j(i,t)t} + \beta_3 \mathbb{I}^H_{j(i,t)t} + Z_{j(i,t)t}\gamma_1 \\ & + Z_{j(i,t-1)}\gamma_2 + \mu_{g(j(i,t))} + \mu_{s(j(i,t))} + \alpha + \xi_{it},\end{aligned} \tag{20}$$

where $j(i,t)$ is the employer where worker i is employed at t, $Young_{j(i,t)t}$ is the young firm indicator, $\mathbb{I}^H_{j(i,t)t}$ is the high-performing firm indicator, $Z_{j(i,t)t}$ is a

[48]The denominator can be translated into the initial dispersion of firm fundamentals, representing the informativeness of signals in each industry. This indicates the degree of uncertainty conditional on this fundamental dispersion, to take into account inherent variations in the informativeness of signals across industries.

[49]I exclude worker fixed effects to control for unobserved worker heterogeneity (and any related sorting effects) but retain firm fixed effects, as these serve as proxies for unobserved firm fundamentals that workers learn. Alternatively, I follow Abowd et al. (1999) by summing the firm fixed effect estimates and residuals for robustness. However, this approach relies on the assumption of exogenous worker mobility, which may be violated if certain worker types sort into specific firms based on unobserved characteristics. In such cases, the residuals estimated in this way may capture this sorting effect, which needs to be removed to properly identify the mechanism in the model.

[50]I additionally include worker skills (the highest education attainment) in robustness test.

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

vector of firm $j(i,t)$'s characteristics, including past-average productivity, current productivity, and employment size (as in the model), and $Z_{j(i,t-1)}$ is a vector of controls for the worker's employer in the previous period, where I use the AKM firm fixed effect associated with the worker's previous employer along with a non-employment indicator as a baseline.[52,53,54] Lastly, industry (g) and state (s) fixed effects are controlled, $\mu_{g(j(i,t))}$ and $\mu_{s(j(i,t))}$.

The novelty in (20) 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 the age effect depends on the firm's average performance over past periods. For low-performing firms, the wage differential for young firms is given by β_1, and for high-performing firms, it is given by $\beta_1 + \beta_2$.

Table 5 shows the results with the full set of controls to be consistent with the model.[55] The first column uses the current firm size, and the second column uses the lagged value. It shows that $\hat{\beta}_1 < 0$, $\hat{\beta}_2 > 0$, and $\hat{\beta}_1 + \hat{\beta}_2 > 0$, where all of these point estimates are statistically significant.[56] The results indicate that high-performing young firms pay more than their otherwise similar mature counterparts, while low performing young firms pay less.

To validate the baseline results, several robustness checks are performed as in

[52]The firm variables have the same values across all workers employed at that firm at t, i.e., workers employed at the SEINs (State Employer Identifier Numbers) associated with the same firm identifier).

[53]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 Appendix F.

[54]The baseline fixed effect is estimated at the SEIN level. As a robustness check, I also use the fixed effects estimated at the firm identifier level. In another robustness test, I use earnings paid by the previous employer.

[55]For the sake of space, I only present the main coefficients. The full results can be found in Appendix Table G2.

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

Table 5: Wage Differentials for Young Firms

	Earnings Residuals	Earnings Residuals
Young	-0.002***	-0.003***
	(0.001)	(0.001)
Young × 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)

Note: 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.

Appendix H. First, firm size is highly correlated with firm age, which may lead the size covariate to absorb firm age effects.[57] To check this, I run regressions without controlling for firm size (with various combinations of firm controls), and the results stay robust as in Appendix Table H4. The second test addresses a potential sampling bias applying the inverse propensity score weights as in Appendix Table H5.[58,59] Third, the second-stage regression is based on estimates from the first-stage regression, which might cause the reported standard errors in Table 5 to be incorrect. To address this, I estimate the standard errors with bootstrapping and confirm the robustness of the statistical significance in Appendix Table H6.[60] Fourth, alternative

[57] Firm size distribution varies by different firm age, e.g., most young firms are small.

[58] The current sample relies on the population of firms with consecutively non-missing observations of revenue data, which drops those with missing data points in their lifecycle.

[59] As Haltiwanger et al. (2017), I use logistic regressions with a dependent variable equal to one if the firm is in the sample and zero otherwise, along with firm characteristics such as firm size, age, employment growth, industry, and a multi-unit status indicator from the universe of the LBD, and compute inverse probability score to weight the regression.

[60] To do so, I draw 5000 random samples with replacement repeatedly from the main dataset, estimate the main coefficients corresponding to these bootstrap samples, form the sampling distribution of the coefficients, and calculate the standard deviation of the sampling distribution for each

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. Appendix Table H7 confirms the robustness after controlling for earnings in the previous job as a proxy of worker tenure or experience.[61] Moreover, worker skills can influence the level of earnings.[62] To address this, I use workers' highest education level as a proxy for skills and include it as an additional control in the first-stage regression. Appendix Table H8 shows the second-stage regression results, robust to earnings residuals that exclude the effect of worker skills. Another unobservable worker characteristic is risk preference as unobserved risks in young firms may still remain even after controlling for firm characteristics.[63] In Appendix Table H9, I further control for the variance of young firm productivity shocks as a proxy for the riskiness of young firms and find robust results. In addition, Appendix Table H10 confirms the robustness with the fixed effects estimated at the firm level with longitudinal firm identifiers.[64] Furthermore, I rerun the regression at the firm level using the firm-level average of earnings residuals and the same set of firm controls in Appendix Table H11.[65] Lastly, Appendix I shows the relationship between earnings differentials and firm hiring or employment growth. I find a negative association between them, independent of firm age, size, and productivity effects. This sup-

coefficient.

[61] The previous earnings can measure workers' positions on the job ladder (or employment status) and the effect of outside option in the model.

[62] If there are sorting patterns between worker skills and firm ages, the results may reflect unobserved worker heterogeneity rather than the uncertainty around young firms.

[63] The earnings differentials in young firms (both high- and low-performing) may reflect worker risk preferences if risk-averse (or risk-loving) workers are sorted into these firms.

[64] The baseline firm fixed effects are estimated at the SEIN level.

[65] This indicates that even after averaging earnings differentials across various worker types and origins, the results remain consistent. This aligns with the model, where firms randomly select workers along their indifference curve. Firm-level earnings differentials move in the same direction as worker-level earnings, controlling for worker-level heterogeneity.

ports the interpretation of the earnings differentials through uncertain job prospects, ruling out other hypotheses such as performance pay or surplus sharing.[66]

4.2 The Impact of Uncertainty on Wages and Aggregate Outcomes

In the model, higher uncertainty drags out the speed of learning and pronounces the wage differentials for young firms. To test this, I include additional interaction terms with the industry-level uncertainty (18) in (20):

$$\begin{aligned}\hat{\epsilon}_{it} \;=\; & \beta_1 Young_{j(i,t)t} \;+\; \beta_2 Young_{j(i,t)t} \times \mathbb{I}^H_{j(i,t)t} \;+\; \beta_3 Young_{j(i,t)t} \times Uncertainty_{g(j,t)t} \\ & +\; \beta_4 Young_{j(i,t)t} \times \mathbb{I}^H_{j(i,t)t} \times Uncertainty_{g(j,t)t} \;+\; \beta_5 Uncertainty_{g(j,t)t} \;+\; \beta_6 \mathbb{I}^H_{j(i,t)t} \\ & +\; \beta_7 \mathbb{I}^H_{j(i,t)t} \times Uncertainty_{g(j,t)t} \;+\; Z_{j(i,t)t}\gamma_1 \;+\; Z_{j(i,t-1)}\gamma_2 \;+\; \mu_{g(j(i,t))} \;+\; \mu_{s(j(i,t))} \\ & +\; \alpha \;+\; \xi_{it},\end{aligned}$$

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.[67] All else is the same as in (20).

The results in Table 6 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 ($\hat{\beta}_3 < 0$).[68,69] This holds for both columns. Appendix Table H12 shows its robustness by using lagged values of uncertainty to mitigate potential reverse causality issue.

Next, I test the aggregate implications with the following regression:

$$Y_{gt} \;=\; \beta Uncertainty_{gt} \;+\; \delta_g \;+\; \delta_t \;+\; \epsilon_{gt}, \tag{21}$$

[66]The results are robust to using $\hat{P}_{jt}$ estimated in (19) and applying inverse propensity score weights, as shown in Appendix Table I13 (panel B) and I14.

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

[68]Refer to Appendix Table G3 for the full table.

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

Table 6: The Effect of Uncertainty on Young Firms' Wage Differentials

	Earnings Residuals	Earnings Residuals
Young	-0.001	-0.001
	(0.001)	(0.001)
$\times$ Uncertainty (at t)	-0.004**	-0.004***
	(0.002)	(0.002)
Young $\times$ High performing	0.012***	0.012***
	(0.002)	(0.002)
$\times$ Uncertainty (at t)	0.006***	0.006***
	(0.002)	(0.002)
Observations	50,170,000	50,170,000
Fixed effects	g, s	g, s
Controls	Full (current size)	Full (lagged size)

Note: The table reports the earnings regression interacted with industry-level uncertainty. The set of controls and fixed effects remain the same as in the baseline regression (20). Each column uses either current or lagged firm size. 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.

Table 7: 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

Note: 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 (18), 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.

where Y_{gt} is either 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.[70] δ_g and δ_t are industry and year fixed effects, respectively.

Table 7 shows that the aggregate variables are dampened in industries with higher uncertainty, where earnings differentials for young firms are amplified in the earlier results.[71] This supports the model's aggregate implications.

5 Conclusion

In this paper, I study how workers' job prospects impact the wage and growth of young firms and the aggregate economy, using a rich model linking firm dynamics to labor market frictions and micro-level administrative data. The paper finds that: i) workers' uncertain job prospects create wage premia for high-performing young firms and wage discounts for low-performing young firms, relative to their observationally identical mature counterparts; ii) reduced uncertainty or search frictions lower wage differentials; and iii) enhance young firm growth and aggregate productivity. In summary, this paper provides a foundation for understanding firm dynamics in conjunction with labor market dynamics through the novel channel of worker job prospects.

[70] High-growth young firms are those above the 90th percentile of the within-industry employment growth distribution and aged five years or less.

[71] Note that this is a cross-sectional association at a high frequency. The results also hold in the long run (using industry fixed effects to align with the model's steady-state economy), as shown in Appendix J.

A Proofs

Proof of Proposition 1 . Lemma 1 can rephrase (9) and (10):

$$
\begin{aligned}
w_j^i = x_j - \beta \mathbb{E}_j \Bigg[\Big(\delta + \big(1-\delta\big)\big(d_j' + (1-d_j')s_j'\big) \Big) U \qquad \text{(A.1)} \\
+(1-\delta)(1-d_j')(1-s_j') \Big(\lambda f(\theta(x_j^{E\prime}))x_j^{E\prime} + \big(1-\lambda f(\theta(x_j^{E\prime}))\big) \tilde{W}_j' \Big) \Bigg] \\
w_j^i = \tilde{W}_j - \beta \mathbb{E}_j \Bigg[\Big(\delta + \big(1-\delta\big)\big(d_j' + (1-d_j')s_j'\big) \Big) U \qquad \text{(A.2)} \\
+(1-\delta)(1-d_j')(1-s_j') \Big(\lambda f(\theta(x_j^{E\prime}))x_j^{E\prime} + \big(1-\lambda f(\theta(x_j^{E\prime}))\big) \tilde{W}_j' \Big) \Bigg].
\end{aligned}
$$

The first term on the right hand side of (A.1) and (A.2) 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.

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:

$$x^U = \kappa - (c^\gamma(\kappa - U))^{\frac{1}{1+\gamma}} \tag{A.3}$$

$$x_k^E(a_k, \tilde{P}_{k,-1}, l_{k,-1}, P_k) = \kappa - (c^\gamma(\kappa - \tilde{W}_k(a_k, \tilde{P}_{k,-1}, l_{k,-1}, P_k)))^{\frac{1}{1+\gamma}} \tag{A.4}$$

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.[72,73] Furthermore, due to workers'

[72] 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.

[73] The market unemployed workers search in x^U is constant with respect to firms' state variables as

non-commitment, employers (j) take into account (A.4) when offering $\tilde{W}_j$ to their incumbent workers. Therefore, $\tilde{W}_j$ (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 (A.1) and (A.2).[74]

Proof of Lemma 2 . Firms choose submarkets satisfying (15), where the complementary slackness condition, $\theta(x)\left(\frac{c}{q(\theta(x))}+x-\kappa\right)=0$, holds for any active labor submarket x with the minimized cost $\kappa \equiv \min\left(\frac{c}{q(\theta(x))}+x\right)$.

At the end, the equilibrium labor submarkets are determined by:

$$\theta(x)=\begin{cases}\left(\left(\frac{\kappa-x}{c}\right)^{\gamma}-1\right)^{\frac{1}{\gamma}} & \text{if} \quad x<\kappa-c \\ 0 \quad \text{if} \quad x\geq\kappa-c, \end{cases} \tag{A.5}$$

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 (5)-(10) can be fully replicated by the following joint surplus maximization:

$V^{init}(a_j,\tilde{P}_{j,-1},l_{j,-1},P_j)=\max_{d_j,s_j,h_j,x_j^E}\delta U l_{j,-1}+(1-\delta)(d_j+(1-d_j)s_j)Ul_{j,-1}+(1-\delta)(1-d_j)\Big(P_j l_j^{\alpha}-c^f-\kappa h_j+(1-s_j)\lambda f(\theta(x_j^E))x_j^E l_{j,-1}+\beta\mathbb{E}_j V^{init}(a_j',\tilde{P}_j,l_j,P_j')\Big)$,

where V_j^{init} is the joint surplus at the beginning of the period.[75]

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;

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.

[74]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).

[75]More details are provided in Appendix C. Similarly, (11) can be rephrased as $\int\max_{d_j^e,l_j^e}(1-d_j^e)\Big(P_j(l_j^e)^{\alpha}-c^f-\kappa l_j^e+\beta\mathbb{E}_jV^{init}(1,\ln P_j,l_j^e,P_j')\Big)dF_e(P_j)-c^e=0$.

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.[76]

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

$$\left[\alpha P_j l_j^{\alpha-1} + \beta \frac{\partial \mathbb{E}_j V_j^{init\prime}}{\partial l_j}\right] - \kappa = 0, \tag{A.6}$$

$$U l_{j,-1} - \lambda f(\theta(x_j{}^E)) x_j^E l_{j,-1} - (1 - \lambda f(\theta(x_j{}^E))) l_{j,-1} \left[\alpha P_j l_j^{\alpha-1} + \beta \frac{\partial \mathbb{E}_j V_j^{init\prime}}{\partial l_j}\right] = 0, \tag{A.7}$$

$$\begin{aligned} &\lambda f'(\theta(x_j^E))\theta'(x_j^E) x_j^E l_{j,-1} + \lambda f(\theta(x_j^E)) l_{j,-1} \\ &-\lambda f'(\theta(x_j^E))\theta'(x_j^E) l_{j,-1} \left[\alpha P_j l_j^{\alpha-1} + \beta \frac{\partial \mathbb{E}_j V_j^{init\prime}}{\partial l_j}\right] = 0. \end{aligned} \tag{A.8}$$

There is no case in which firms hire and separate workers at the same time. Suppose $h_j > 0$. Combining (A.5), (A.6), (A.8), 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 (A.8)) 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 A.7) negative and firms never choose $s_j > 0$. Similarly, contracting firms ($s_j > 0$) will never choose $h_j > 0$ as (A.7) makes the marginal value of $h_j > 0$ ($\frac{\partial V_j{}^{init}}{\partial h_j}$, the left-hand side of (A.6)) 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: $x_j^E = \tilde{W}_j = \kappa - c$[77];

[76] These cutoffs are generated due to the vacancy cost and operating fixed cost and endogenously determined by the beginning-of-period state variables $(a_j, \tilde{P}_{j,-1}, l_{j,-1})$ before the current productivity draw P_j. See more details in Appendix D.

[77] 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 (A.8)) 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 would not just stay inactive but also not allow workers to quit, i.e. $l_j = l_{j,-1}$.

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

$$x_j^E + \frac{f(\theta(x_j^E))}{f'(\theta(x_j^E))\theta'(x_j^E)} \tag{A.9}$$
$$-\Big[\alpha P_j \Big((1-\lambda f(\theta(x_j^E)))l_{j,-1}\Big)^{\alpha-1} + \beta \frac{\partial \mathbb{E}_j V_j^{init\prime}}{\partial l_j}|_{l_j=(1-\lambda f(\theta(x_j^E)))l_{j,-1}}\Big] = 0$$

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

$$\kappa - U = c\Big[(1+\theta(x_j^E)^\gamma)^{1+\frac{1}{\gamma}} - \lambda\theta(x_j^E)^{1+\gamma}\Big] \tag{A.10}$$
$$\tilde{W}_j = \kappa - (\kappa - x_j^E)^{1+\gamma} c^{-\gamma}$$
$$\Big[\alpha P_j l_j^{\alpha-1} + \beta \frac{\partial \mathbb{E}_j V_j^{init\prime}}{\partial l_j}\Big] = \frac{U - \lambda x_j^E \Big(\theta(x_j^E)(1+\theta(x_j^E)^\gamma)^{-\frac{1}{\gamma}}\Big)}{1 - \lambda\Big(\theta(x_j^E)(1+\theta(x_j^E)^\gamma)^{-\frac{1}{\gamma}}\Big)}. \tag{A.11}$$

Lastly, let's define $\hat{W}_j \equiv \Bigg(s_j U + (1-s_j)\big(\lambda f(\theta(x_j^E))x_j^E + \big(1-\lambda f(\theta(x_j^E))\big)\tilde{W}_j\big)\Bigg)$ 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 $\hat{W}_j^{quit} = \Bigg(\lambda f(\theta(x_j^E))x_j^E + \big(1-\lambda f(\theta(x_j^E))\big)\tilde{W}_j\Bigg)$; iii) workers at contracting employers (with lay-offs) or in the unemployment pool have the lowest $\hat{W}_j$, where $\hat{W}_j^{layoff} = \Bigg(s_j U + (1-s_j)\big(\lambda f(\theta(x_j^E))x_j^E + \big(1-\lambda f(\theta(x_j^E))\big)\tilde{W}_j\big)\Bigg)$ 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 (A.4), 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 (A.9). Also, the marginal value of s_j (the left-hand side of (A.7)) 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 (A.10). With (A.10), $U = x_j^E - \theta(x_j^E)^\gamma(\kappa - x_j^E) + \lambda c\theta(x_j^E)^{1+\gamma}$, and $\hat{W}_j^{layoff} = \hat{W}_j^{unemp}$, $\forall s_j \in [0,1]$. It proves $\hat{W}_j^{unemp} = \hat{W}_j^{layoff} \leq \hat{W}_j^{quit} \leq \hat{W}_j^{hire,noquit}$.[78]

Proof of Proposition 2 . Following Proposition 1, along with the state contingency of contracts, workers' non-commitment and optimality condition (14), and the posteriors (1), given the worker's previous employment status, the wage is a function of firm state variables $(a_j, \tilde{P}_{j,-1}, l_{j,-1}, P_j)$.

Proof of Proposition 3 . Given (1) and the log normality assumption, there is a point $\hat{P} \equiv \frac{\bar{\nu}^{old}\sigma^{young} - \bar{\nu}^{young}\sigma^{old}}{\sigma^{young} - \sigma^{old}}$ 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 $\ln P \geq (\leq)\hat{P}$.[79] This implies young (old) firms' posterior distribution exhibits first-order stochastic dominance (FOSD) when $\ln P \geq (\leq)\hat{P}$.

Let $\bar{\bar{P}}^H$ and $\bar{\bar{P}}^L$ 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}.[80] First, suppose $\tilde{P} \geq \bar{\bar{P}}^H$. As $\hat{P}$ is increasing in $\tilde{P}$, for any $\tilde{P} \geq \bar{\bar{P}}^H$, $\hat{P} \geq \max[\mathcal{P}^q(a^{young}, \tilde{P}, l_{-1}), \mathcal{P}^q(a^{old}, \tilde{P}, l_{-1})]$ holds. Next, it can be derived that: $\int_{\hat{P}} \hat{W}^{old} dF^{old}(\ln P) = \int_{\hat{P}} \hat{W}^{young} dF^{young}(\ln P) =$

[78] 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 (A.4), 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. Appendix D 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.

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

[80] The productivity cutoffs depend on $(a_j, \tilde{P}_{j,-1}, l_{j,-1})$. As shown in Appendix D, 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 $\tilde{P}_{j,-1}$.

$\hat{W}^{hire,noquit}(1 - F_z(\bar{\nu}^{old} - \bar{\nu}^{young}))$, where $F_z(\cdot)$ is the standardized normal cdf, and $\hat{W}^{hire,noquit} = \kappa - c$ is constant across firms.[81] The FOSD of F^{old} implies $\int^{\hat{P}} \hat{W}^{old} dF^{old}(\ln P) \geq \int^{\hat{P}} \hat{W}^{old} dF^{young}(\ln P) \geq \int^{\hat{P}} \hat{W}^{young} dF^{young}(\ln P)$ as $\hat{W}_j$ weakly increases in P_j. Thus, $\int \hat{W}^{old} dF^{old}(\ln P) \geq \int \hat{W}^{young} dF^{young}(\ln P)$ is derived. Similarly, if $\tilde{P} \leq \bar{\tilde{P}}^L$, $\int^{\hat{P}} \hat{W}^{young} dF^{young}(\ln P) = \int^{\hat{P}} \hat{W}^{old} dF^{old}(\ln P)$ $= \hat{W}^{layoff} F_z(\bar{\nu}^{old} - \bar{\nu}^{young})$ 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 (A.8) and (A.11), is also constant across firms. Given the FOSD of F^{young}, $\int_{\hat{P}} \hat{W}^{young} dF^{young}(\ln P) \geq \int_{\hat{P}} \hat{W}^{young} dF^{old}(\ln P) \geq \int_{\hat{P}} \hat{W}^{old} dF^{old}(\ln P)$. This proves $\int \hat{W}^{old} dF^{old}(\ln P) \leq \int \hat{W}^{young} dF^{young}(\ln P)$. Linking these results to Proposition 1 completes the proof for wages.

B Bayesian Learning

Suppose that initial prior is $\nu_j \sim N(\bar{\nu}_0, \sigma_0^2)$, and there is an observation of $\ln P_{jt} = \nu_j + \varepsilon_{jt}$ such that $\varepsilon_{jt} \sim N(0, \sigma_\varepsilon^2)$. Following the Bayes' rule, $f(\nu_j | \ln P_{jt}) \propto f(\nu_j) f(\ln P_{jt} | \nu_j)$, we have:

$$
\begin{aligned}
f(\nu_j | \ln P_{jt}) &\propto f(\nu_j) f(\ln P_{jt} | \nu_j) \\
&= \left(\frac{1}{\sqrt{2\pi\sigma_0^2}} \exp\left(-\frac{(\nu_j - \bar{\nu}_0)^2}{2\sigma_0^2} \right) \right) \left(\frac{1}{\sqrt{2\pi\sigma_\varepsilon^2}} \exp\left(-\frac{(\ln P_{jt} - \nu_j)^2}{2\sigma_\varepsilon^2} \right) \right) \\
&\propto \left(\frac{1}{\sqrt{2\pi\sigma_0^2\sigma_\varepsilon^2}} \exp\left(-\frac{\left(\nu_j - \left(\frac{\sigma_\varepsilon^2 \bar{\nu}_0 + \sigma_0^2 \ln P_{jt}}{\sigma_\varepsilon^2 + \sigma_0^2} \right) \right)^2}{2 \frac{\sigma_0^2 \sigma_\varepsilon^2}{\sigma_\varepsilon^2 + \sigma_0^2}} \right) \right),
\end{aligned}
$$

which implies:

$$
f(\nu_j | \ln P_{jt}) \sim N\left(\frac{\sigma_\varepsilon^2 \bar{\nu}_0 + \sigma_0^2 \ln P_{jt}}{\sigma_\varepsilon^2 + \sigma_0^2}, \frac{\sigma_0^2 \sigma_\varepsilon^2}{\sigma_\varepsilon^2 + \sigma_0^2} \right).
$$

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

Thus, the mean and standard deviation of the posterior distribution are given by:

$$\bar{\nu}_{jt} = \frac{\sigma_\varepsilon^2 \bar{\nu}_{jt-1} + \sigma_{jt-1}^2 \ln P_{jt}}{\sigma_{jt-1}^2 + \sigma_\varepsilon^2} = \frac{\frac{\bar{\nu}_{jt-1}}{\sigma_{jt-1}^2} + \frac{\ln P_{jt}}{\sigma_\varepsilon^2}}{\frac{1}{\sigma_{jt-1}^2} + \frac{1}{\sigma_\varepsilon^2}}, \tag{B.12}$$

$$\sigma_{jt}^2 = \frac{\sigma_{jt-1}^2 \sigma_\varepsilon^2}{\sigma_{jt-1}^2 + \sigma_\varepsilon^2} = \frac{1}{\frac{1}{\sigma_{jt-1}^2} + \frac{1}{\sigma_\varepsilon^2}}. \tag{B.13}$$

By iterating (B.12) and (B.13) backward, (1) in the main text can be derived.

Note that the posterior mean in (1) is a weighted sum of the initial prior mean and the average observed productivity over past periods, with weights determined by firm age. The mean increases with average productivity, where higher average productivity enhances prospects about firms. On the other hand, the posterior mean increases with firm age only if the firm's average productivity is above the initial cross-sectional mean ($\tilde{P}_{jt-1} > \bar{\nu}_0$), while it decreases with firm age if the firm's average productivity is below the cross-sectional mean ($\tilde{P}_{jt-1} < \bar{\nu}_0$).[82] The posterior variance in (1) decreases with firm age, and the posterior converges to a degenerate distribution centered at the true type ν_j as the firm ages.

Furthermore, the following relationships between the two sufficient statistics and the posterior mean at the beginning of each period t can be derived:

$$\frac{\partial \bar{\nu}_{jt-1}}{\partial \tilde{P}_{jt-1}} = \frac{a_{jt} \frac{1}{\sigma_\varepsilon^2}}{\frac{1}{\sigma_0^2} + a_{jt} \frac{1}{\sigma_\varepsilon^2}} > 0 \tag{B.14}$$

$$\frac{\partial \bar{\nu}_{jt-1}}{\partial a_{jt}} = \frac{(\tilde{P}_{jt-1} - \bar{\nu}_0)}{\sigma_0^2 \sigma_\varepsilon^2 \left(\frac{1}{\sigma_0^2} + a_{jt} \frac{1}{\sigma_\varepsilon^2} \right)^2} \begin{cases} \geq 0 & \text{if} \quad \tilde{P}_{jt-1} \geq \bar{\nu}_0 \\ < 0 & \text{if} \quad \tilde{P}_{jt-1} < \bar{\nu}_0 \end{cases}. \tag{B.15}$$

Equation (B.14) implies that the posterior mean increases with the average productivity level. As firms are observed to have higher average productivity, their prospects

[82] In other words, a higher age indicates a better (worse) inferred type for the former (latter) case.

improve. Moreover, (B.15) shows that firm age affects job prospects differently depending on the firm's past-average productivity. Specifically, if firm j's average productivity is above the initial cross-sectional mean, a higher age implies a better inferred type, while if a firm's average productivity is below the cross-sectional mean, a higher age implies a worse inferred type.

Also, one can derive the following relationship between firm age and the posterior standard deviation:

$$\frac{\partial \sigma^2_{jt-1}}{\partial a_{jt}} = -\frac{1}{\sigma^2_\varepsilon\left(\frac{1}{\sigma^2_0} + a_{jt}\frac{1}{\sigma^2_\varepsilon}\right)^2} < 0. \tag{B.16}$$

This implies that as a firm ages, learning becomes less noisy, and the posterior converges to a degenerate distribution centered at the true type ν_j.

C Joint Surplus Maximization

As in the main text, I drop time subscripts henceforth. Solving the firms' problem, the value function (5) can be fully replicated by the following joint surplus maximization:

$$V^{prod}(a_j, \tilde{P}_{j,-1}, l_{j,-1}, P_j) = \max_{d'_j, s'_j, x'_j, x^{E\prime}_j, h'_j} P_j l^\alpha_j - c_f + \beta \mathbb{E}_j \Bigg[(1-\delta)(1-d'_j)\Big(V^{prod}(a'_j, \tilde{P}_j, l_j, P'_j)$$
$$- \left(x'_j + \frac{c}{q(\theta(x'_j))}\right)h'_j + (1-s'_j)\lambda f(\theta(x^{E\prime}_j))x^{E\prime}_j l_j\Big) + \Big(\delta + (1-\delta)\big(d'_j + (1-d'_j)s'_j\big)\Big)U' l_j\Bigg],$$

where $V^{prod}_j \equiv J^{prod}_j + x_j h_j + \tilde{W}_j(1-s_j)(1-\lambda f\big(\theta(x^E_j)\big))l_{j,-1}$, J^{prod}_j is the firm value function at the production stage after search and matching, and $\mathbf{\Omega_j^{-w}} = \{d'_j, s'_j, \tilde{W}'_j\}$ denotes the contract abstracting from the wage w^i_j.

Given that choice variables are contingent on future productivity, it can be transformed using the following value function, defined at the beginning of each period:

$$V_j^{init}(a_j, \tilde{P}_{j,-1}, l_{j,-1}, P_j) = \max_{d_j, s_j h_j, x_j^E} \delta U l_{j,-1} + (1-\delta)(d_j + (1-d_j)s_j)U l_{j,-1}$$
$$+(1-\delta)(1-d_j)\Big(P_j l_j^\alpha - c^f - \kappa h_j + (1-s_j)\lambda f(\theta(x_j^E))x_j^E l_{j,-1} + \beta \mathbb{E}_j V_j^{init}(a_j', \tilde{P}_j, l_j, P_j')\Big).$$

Note that the first term $\delta U l_{j,-1}$ is independent of the variables being maximized and $(1-\delta)$ in the remaining two terms simply scales the objective function. The problem can first be solved for s_j, h_j, and x_j^E, maximizing:

$$\max_{s_j, h_j, x_j^E} s_j U l_{j,-1} + P_j l_j^\alpha - c^f - \kappa h_j + (1-s_j)\lambda f(\theta(x_j^E))x_j^E l_{j,-1} + \beta \mathbb{E}_j V_j^{init}(a_j', \tilde{P}_j, l_j, P_j'). \tag{C.17}$$

And then $d_j = 1$ if $U l_{j,-1}$ is greater than the value (C.17), and $d_j = 0$, otherwise.

In a similar fashion, the free-entry condition (11) can be rephrased as:

$$\int \max_{d_j^e, l_j^e} (1-d_j^e)\Big(P_j (l_j^e)^\alpha - c^f - \kappa l_j^e + \beta \mathbb{E}_j V^{init}(1, \ln P_j, l_j^e, P_j')\Big) dF_e(P_j) - c^e = 0. \tag{C.18}$$

D Productivity Cutoffs

Deriving the four endogeneous productivity cutoffs, $\mathcal{P}_j^h$, $\mathcal{P}_j^q$, $\mathcal{P}_j^l$, and $\mathcal{P}_j^x$, follow the following first-order conditions with respect to h_j, s_j, and x_j^E:

$$\left[\alpha P_j l_j^{\alpha-1} + \beta \frac{\partial \mathbb{E}_j V_j^{init\prime}}{\partial l_j}\right] - \kappa = 0, \tag{D.19}$$

$$U - \lambda f(\theta(x_j^E))x_j^E - (1 - \lambda f(\theta(x_j^E)))\left[\alpha P_j l_j^{\alpha-1} + \beta \frac{\partial \mathbb{E}_j V_j^{init\prime}}{\partial l_j}\right] = 0, \tag{D.20}$$

$$x_j^E + \frac{f(\theta(x_j^E))}{f'(\theta(x_j^E))\theta'(x_j^E)} - \left[\alpha P_j l_j^{\alpha-1} + \beta \frac{\partial \mathbb{E}_j V_j^{init\prime}}{\partial l_j}\right] = 0. \tag{D.21}$$

First, to determine the hiring cutoff, (D.19) needs to be evaluated at $l_j = l_{j,-1}$, where firms are indifferent between hiring and not hiring. Given the state variables

$(a_j, \tilde{P}_{j,-1}, l_{j,-1})$, the hiring decision depends on whether the marginal value of hiring, represented by the first term of (D.19), exceeds the cost of hiring κ or not. If P_j falls within a range where the marginal value becomes less than κ, the firm opts to stop hiring. The hiring cutoff is thus defined as the productivity level P_j at which the marginal value of hiring equals the cost, making $h_j = 0$ the optimal choice. Below this threshold, the marginal value derived from hiring new workers is insufficient to justify the cost, and firms will refrain from hiring workers.

Therefore, the hiring productivity cutoff $\mathcal{P}_j^h$ is determined by equating the marginal value of hiring to the cost of hiring κ, as expressed in the following equation:

$$\left[\alpha \mathcal{P}_j^h l_{j,-1}^{\alpha-1} + \beta \frac{\partial \mathbb{E}_j V_j^{init\prime}}{\partial l_j}\Big|_{\tilde{P}_j = \frac{a_j \tilde{P}_{j,-1} + \mathcal{P}_j^h}{a_j+1}, l_j = l_{j,-1}}\right] = \kappa, \tag{D.22}$$

where the expectation $\mathbb{E}_j(\cdot)$ is formed over P_j' based on the firm's and its workers' posterior beliefs at the start of the next period. The beliefs incorporate the updated firm age $a_j + 1$ and average productivity $\tilde{P}_j = \frac{a_j \tilde{P}_{j,-1} + \mathcal{P}_j^h}{a_j+1}$.

The quitting cutoff, $\mathcal{P}_j^q$, delineates the range of productivity levels where firms begin allowing workers to quit. Note that firms would not hire workers when

$$\left[\alpha P_j \Big((1 - \lambda f(\theta(x_j^E))) l_{j,-1}\Big)^{\alpha-1} + \beta \frac{\partial \mathbb{E}_j V_j^{init\prime}}{\partial l_j}\Big|_{l_j = (1-\lambda f(\theta(x_j^E))) l_{j,-1}}\right] < \kappa, \tag{D.23}$$

as before. At the same time, if the marginal value of x^E is still high enough, firms optimally set x^E to its upper bound. This condition arises when the marginal value of x^E is positive, which corresponds to the left-hand side of (D.21). This condition can be rephrased as:

$$\left[\alpha P_j l_j^{\alpha-1} + \beta \frac{\partial \mathbb{E}_j V_j^{init\prime}}{\partial l_j}\right] > x_j^E + \frac{f(\theta(x_j^E))}{f'(\theta(x_j^E))\theta'(x_j^E)},$$

given $\theta'(x_j^E) < 0$ and $f'(\theta(x_j^E)) < 0$. Also, given $x_j^E = \kappa - c$, this becomes

$$\left[\alpha P_j l_j^{\alpha-1} + \beta \frac{\partial \mathbb{E}_j V_j^{init'}}{\partial l_j}\right] > \kappa - c. \tag{D.24}$$

Combining (D.23) and (D.24), firms would stay inactive without allowing quits in the following range:

$$\kappa - c < \left[\alpha P_j l_{j,-1}^{\alpha-1} + \beta \frac{\partial \mathbb{E}_j V_j^{init'}}{\partial l_j}|_{l_j = l_{j,-1}}\right] < \kappa. \tag{D.25}$$

In other words, the quitting cutoff $\mathcal{P}_j^q$ is determined by the following equation:

$$\left[\alpha \mathcal{P}_j^q l_{j,-1}^{\alpha-1} + \beta \frac{\partial \mathbb{E}_j V_j^{init'}}{\partial l_j}|_{\tilde{P}_j = \frac{a_j \tilde{P}_{j,-1} + \mathcal{P}_j^q}{a_j+1}, l_j = l_{j,-1}}\right] = \kappa - c, \tag{D.26}$$

below which firms start allowing quits. As before, the expectation $\mathbb{E}_j(\cdot)$ is formed over P_j' based on the firm's and its workers' posterior belief with $a_j + 1$ and $\tilde{P}_j' = \frac{a_j \tilde{P}_{j,-1} + \mathcal{P}_j^q}{a_j+1}$.

Lastly, in regards to the layoff cutoff, it is determined by (D.20) evaluated at $l_j = (1 - \lambda f(\theta(x_j^E)))l_{j,-1}$ where x_j^E is the root of (D.21). Similar to the hiring cutoff, given $(a_j, \tilde{P}_{j,-1}, l_{j,-1})$, if P_j lies in a range in which the marginal value of layoffs (the left-hand side of (D.20)) is lower, then firms will no longer lay off any workers. Therefore, the cutoff is determined at the point where it is optimal to set $s_j = 0$ in the separating firms' problem, above which firms would never lay off workers. The following equation thus determines the layoff productivity cutoff $\mathcal{P}_j^l$:

$$\left[\alpha \mathcal{P}_j^l((1 - \lambda f(\theta(x_j^E)))l_{j,-1})^{\alpha-1} + \beta \frac{\partial \mathbb{E}_j V_j^{init'}}{\partial l_j}|_{\tilde{P}_j = \frac{a_j \tilde{P}_{j,-1} + \mathcal{P}_j^l}{a_j} + 1, l_j = (1-\lambda f(\theta(x_j^E)))l_{j,-1}}\right]$$
$$= \frac{U - \lambda x_j^E \left(\theta(x_j^E)(1+\theta(x_j^E)^\gamma)^{-\frac{1}{\gamma}}\right)}{1 - \lambda\left(\theta(x_j^E)(1+\theta(x_j^E)^\gamma)^{-\frac{1}{\gamma}}\right)}, \tag{D.27}$$

where x_j^E is the root of (D.21) with the set of state variables $(a_j, \tilde{P}_{j,-1}, l_{j,-1}, \mathcal{P}_j^l)$. The expectation $\mathbb{E}_j(\cdot)$ is formed over P_j' based on the firm's and its workers' posteriors with a_j+1 and $\tilde{P}_j' = \frac{a_j \tilde{P}_{j,-1} + \mathcal{P}_j^l}{a_j+1}$ as before.

The following part shows how the productivity cutoffs vary across firms with different posteriors. To understand this, we first need to examine how the future expected marginal value of labor input, $\left(\frac{\partial \mathbb{E} V^{init}(a_j', \tilde{P}_j, l_j, P_j')}{\partial l_j}\right)$, varies among firms. This variation, as we will show, depends on firms' employment status, preserving the same ranking as the future expected value of workers, as discussed in the earlier section.

D.1 Hiring Firms: $s_j = 0$ and $h_j > 0$

For hiring firms, their value function becomes:

$$V_j^{init}(a_j, \tilde{P}_{j,-1}, l_{j,-1}, P_j) = \delta U l_j + (1-\delta)\Big[P_j {l_j}^{\alpha} - c^f - \kappa h_j + \beta \mathbb{E}_j V^{init}(a_j', \tilde{P}_j, l_j, P_j')\Big],$$

where $h_j \equiv h(a_j, \tilde{P}_{j,-1}, l_{j,-1}, P_j)$ is the firm's hiring decision rule and $l_j \equiv h_j + l_{j,-1}$. Then, the derivative of the value function with respect to l_j is:

$$\begin{aligned} \frac{\partial V^{init}(a_j, \tilde{P}_{j,-1}, l_{j,-1}, P_j)}{\partial l_{j,-1}} &= \delta U + (1-\delta)\Big[\alpha P_j {l_j}^{\alpha-1} + \beta \frac{\partial \mathbb{E}_j V^{init}(a_j', \tilde{P}_j, l_j, P_j')}{\partial l_j}\Big] \\ &+ (1-\delta)\frac{\partial h_j}{\partial l_{j,-1}}\Big[\alpha P_j {l_j}^{\alpha-1} + \beta \frac{\partial \mathbb{E}_j V^{init}(a_j', \tilde{P}_j, l_j, P_j')}{\partial l_j} - \kappa\Big], \end{aligned}$$

where the first line represents the direct effect of $l_{j,-1}$, and the second line is an indirect effect of $l_{j,-1}$ through its optimal hiring on the value function. With the first-order condition for hiring, (D.19), the indirect effect becomes zero, consistent with the envelope theorem. This simplifies the derivative of the value function with respect to $l_{j,-1}$ as follows:

$$\frac{\partial V^{init}(a_j, \tilde{P}_{j,-1}, l_{j,-1}, P_j)}{\partial l_{j,-1}} = \delta U + (1-\delta)\kappa. \tag{D.28}$$

D.1.1 Inactive Firms: $s_j = 0$ and $h_j = 0$

Next, consider inactive firms who do not allow quits, where $h_j = 0$, $s_j = 0$, $x_j^E = 0$, and the employment size remains constant at $l_j = l_{j,-1}$. Thus, the firm's value function becomes:

$$V^{init}(a_j, \tilde{P}_{j,-1}, l_{j,-1}, P_j) = \delta U l_{j,-1} + (1-\delta)\Big[P_j l_{j,-1}^{\alpha} - c^f + \beta \mathbb{E}_j V^{init}(a_j', \tilde{P}_j, l_j, P_j')\Big],$$

and the first derivative of it with respect to $l_{j,-1}$ is

$$\frac{\partial V^{init}(a_j, \tilde{P}_{j,-1}, l_{j,-1}, P_j)}{\partial l_{j,-1}} = \delta U + (1-\delta)\Big[\alpha P l_{j,-1}^{\alpha-1} + \beta \frac{\partial \mathbb{E}_j V^{init}(a_j', \tilde{P}_j, l_j, P_j')}{\partial l_{j,-1}}\Big].$$

Note that this case can only happen with the range (D.25), and thus their marginal value of labor falls within the range of $[\kappa - c, \kappa]$ as follows:

$$\delta U + (1-\delta)(\kappa - c) \leq \frac{\partial V^{init}(a_j, \tilde{P}_{j,-1}, l_{j,-1}, P_j)}{\partial l_{j,-1}} \leq \delta U + (1-\delta)\kappa. \tag{D.29}$$

Now, consider the case of inactive firms that allow quits. Their value function is as follows:

$$\begin{aligned} V^{init}(a_j, \tilde{P}_{j,-1}, l_{j,-1}, P_j) &= \delta U l_{j,-1} + (1-\delta)\Big[P_j {l_j}^{\alpha} - c^f + \lambda f(\theta(x_j^E)) x_j^E l_{j,-1} \\ &+ \beta \mathbb{E}_j V^{init}(a_j', \tilde{P}_j, l_j, P_j')\Big], \end{aligned}$$

where $x_j^E \equiv x_j^E(a_j, \tilde{P}_{j,-1}, l_{j,-1}, P_j)$ is their optimal retention choice and $l_j \equiv (1 - \lambda f(\theta(x_j^E(a_j, \tilde{P}_{j,-1}, l_{j,-1}, P_j))))l_{j,-1}$.

Getting the derivative as before, the following can be obtained:

$$
\begin{aligned}
& \frac{\partial V^{init}(a_j, \tilde{P}_{j,-1}, l_{j,-1}, P_j)}{\partial l_{j,-1}} \\
= \;& \delta U + (1-\delta)\Big[(1-\lambda f(\theta(x_j^E)))\Big(\alpha P_j {l_j}^{\alpha-1} + \beta \frac{\partial \mathbb{E}_j V^{init}(a'_j, \tilde{P}_j, l_j, P'_j)}{\partial l_j}\Big) + \lambda f(\theta(x_j^E)) x_j^E\Big] \\
+ \;& (1-\delta)\frac{\partial x_j^E}{\partial l_{j,-1}}\Big[-\lambda f'(\theta)\theta'(x_j^E) l_{j,-1}\Big(\alpha P_j {l_j}^{\alpha-1} + \beta \frac{\partial \mathbb{E}_j V^{init}(a'_j, \tilde{P}_j, l_j, P'_j)}{\partial l_j}\Big) \\
+ \;& \lambda f(\theta(x_j^E)) l_{j,-1} + \lambda f'(\theta)\theta'(x_j^E) x_j^E l_{j,-1}\Big].
\end{aligned}
$$

Here, the first line represents the direct effect of $l_{j,-1}$, and the last two lines correspond to the indirect effect of $l_{j,-1}$ through its optimal retention on the value function. As before, the indirect effect becomes zero through the envelope theorem. Thus, the terms can be rephrased as:

$$
\frac{\partial V^{init}(a_j, \tilde{P}_{j,-1}, l_{j,-1}, P_j)}{\partial l_{j,-1}} = \delta U + (1-\delta)\Big[x_j^E + \frac{(1-\lambda f(\theta(x_j^E)))f(\theta(x_j^E))}{f'(\theta)\theta'(x_j^E)}\Big].
$$

Note that this term must satisfy the following range:

$$
U \leq \frac{\partial V^{init}(a_j, \tilde{P}_{j,-1}, l_{j,-1}, P_j)}{\partial l_{j,-1}} \leq \delta U + (1-\delta)(\kappa - c). \tag{D.30}
$$

The upper bound comes from $f'(\theta)\theta'(x_j^E) < 0$ and $x_j^E \leq \kappa - c$. The lower bound is derived from the fact that this firm never finds $s_j > 0$ to be optimal, which is consistent to say the left-hand side of (D.20) being strictly negative for any $s_j > 0$ or zero when $s_j = 0$. Combining this with (D.21), it can be proved that:

$$
U \leq \Big[x_j^E + \frac{(1-\lambda f(\theta(x_j^E)))f(\theta(x_j^E))}{f'(\theta)\theta'(x_j^E)}\Big]
$$

which gives the lower bound in (D.30).

D.1.2 Separating Firms with Layoffs: $s_j > 0$ and $h_j = 0$

For firms that separate workers with explicit layoffs, their value function is:

$$\begin{aligned} V^{init}(a_j, \tilde{P}_{j,-1}, l_{j,-1}, P_j) &= \delta U l_{j,-1} + (1-\delta)\Big[s_j U l_{j,-1} + P_j {l_j}^{\alpha} - c^f + (1-s_j)\lambda f(\theta(x_j^E)) x_j^E l_{j,-1} \\ &+ \beta \mathbb{E}_j V^{init}(a_j', \tilde{P}_j, l_j, P_j')\Big], \end{aligned}$$

where $s_j \equiv s(a_j, \tilde{P}_{j,-1}, l_{j,-1}, P_j)$ is their layoff decision, $x_j^E \equiv \mathbf{x^E}(a_j, \tilde{P}_{j,-1}, l_{j,-1}, P_j)$ is their retention decision, and $l_j \equiv (1-s_j)(1-\lambda f(\theta(x_j^E)))l_{j,-1}$.

Making the first derivative of it with respect to $l_{j,-1}$, it can be obtained that:

$$\begin{aligned} &\frac{\partial V^{init}(a_j, \tilde{P}_{j,-1}, l_{j,-1}, P_j)}{\partial l_{j,-1}} = \delta U + (1-\delta)\Big[s_j U \\ +\;& (1-s_j)(1-\lambda f(\theta(x_j^E)))\Big(\alpha P_j {l_j}^{\alpha-1} + \beta \frac{\partial \mathbb{E}_j V^{init}(a_j', \tilde{P}_j, l_j, P_j')}{\partial l_j}\Big)(1-s_j)\lambda f(\theta(x_j^E))x_j^E\Big] \\ +\;& (1-\delta)\frac{\partial s_j}{\partial l_{j,-1}}\Big[U l_{j,-1} - (1-\lambda f(\theta(x_j^E)))l_{j,-1}\Big(\alpha P_j {l_j}^{\alpha-1} + \beta \frac{\partial \mathbb{E}_j V^{init}(a_j', \tilde{P}_j, l_j, P_j')}{\partial l_j}\Big) \\ -\;& \lambda f(\theta(x_j^E))x_j^E l_{j,-1}\Big] \\ +\;& (1-\delta)(1-s_j)\frac{\partial x_j^E}{\partial l_{j,-1}}\Big[-\lambda f'(\theta)\theta'(x_j^E)l_{j,-1}\Big(\alpha P_j {l_j}^{\alpha-1} + \beta \frac{\partial \mathbb{E}_j V^{init}(a_j', \tilde{P}_j, l_j, P_j')}{\partial l_j}\Big) \\ +\;& \lambda f(\theta(x_j^E))l_{j,-1} + \lambda f'(\theta)\theta'(x_j^E)x_j^E l_{j,-1}\Big], \end{aligned}$$

where the first two lines represent the direct effect of $l_{j,-1}$, the third and fourth lines correspond to the indirect effect of $l_{j,-1}$ through its optimal layoffs, and the last two lines are the indirect effect of $l_{j,-1}$ through its optimal retention on the value function. Note that, using the optimal conditions (which again implies the envelope theorem), (D.20) and (D.21) make the indirect effects zero, and the first line simplifies further. Ultimately, the derivative becomes:

$$\frac{\partial V^{init}(a_j, \tilde{P}_{j,-1}, l_{j,-1}, P_j)}{\partial l_{j,-1}} = U. \tag{D.31}$$

D.1.3 Exiting firms: $d_j = 1$

Lastly, for exiting firms, their value function is:

$$V^{init}(a_j, \tilde{P}_{j,-1}, l_{j,-1}, P_j) = U l_{j,-1},$$

and the derivative with respect to $l_{j,-1}$ is:

$$\frac{\partial V^{init}(a_j, \tilde{P}_{j,-1}, l_{j,-1}, P_j)}{\partial l_{j,-1}} = U. \tag{D.32}$$

Combining (D.28), (D.29), (D.30), (D.31), and (D.32), it can be proved that for $\frac{\partial V^{init}(a_j, \tilde{P}_{j,-1}, l_{j,-1}, P_j)}{\partial l_{j,-1}}$, hiring firms have the highest value, inactive firms without quits have the second highest value, quitting firms have the third highest value, and firms laying off workers or exiting have the lowest value.

$$\frac{\partial V^{init}(a_j, \tilde{P}_{j,-1}, l_{j,-1}, P_j)}{\partial l_{j,-1}} = \begin{cases} \delta U + (1-\delta)\kappa \text{ if } P_j > \mathcal{P}_j^h \\ \delta U + (1-\delta)(\kappa - c) \text{ if } \mathcal{P}_j^q < P_j < \mathcal{P}_j^h \\ \delta U + (1-\delta)\Big[x_j^E + \frac{(1-\lambda f(\theta(x_j^E)))f(\theta(x_j^E))}{f'(\theta)\theta'(x_j^E)}\Big] \text{ if } \mathcal{P}_j^l < P_j < \mathcal{P}_j^q \\ U \text{ if } P_j < \mathcal{P}_j^l, \end{cases} \tag{D.33}$$

From (D.21), it can be derived that higher P_j, holding all else constant, should increase the optimal x_j^E for firms experiencing worker quits in the range $\mathcal{P}_j^l < P_j < \mathcal{P}_j^q$. This conclusion arises because higher P_j increases both the marginal revenue and the posterior mean $\tilde{P} = \frac{a_j P_{j,-1} + \ln P_j}{a_j + 1}$, which firms take into account when forming the expected marginal value of a labor input. To accommodate these changes, x_j^E must be adjusted upward as the first two terms $x_j^E + \frac{f(\theta(x_j^E))}{f'(\theta(x_j^E))\theta'(x_j^E)}$ in (D.21) need to increase, and this expression is an increasing function of x_j^E. Furthermore, in (D.33), it can be shown that: $\frac{\partial\left[x_j^E + \frac{(1-\lambda f(\theta(x_j^E)))f(\theta(x_j^E))}{f'(\theta)\theta'(x_j^E)}\right]}{\partial x_j^E} = 1 + (1 - \lambda)\gamma c^{-\gamma}(\kappa - x_j^E)^{\gamma-1} > 0$, for firms in the range $\mathcal{P}_j^l < P_j < \mathcal{P}_j^q$.

Altogether, this implies that $\frac{\partial V^{init}(a_j, \tilde{P}_{j,-1}, l_{j,-1}, P_j)}{\partial l_{j,-1}}$ is a weakly increasing function of P_j, all else equal. Therefore, firms that are more likely to draw higher P_j' and expand in the next period will obtain a higher expected future marginal value of a labor input, $\frac{\partial \mathbb{E}_j V_j^{init}(a_j', \tilde{P}_j, l_j, P_j')}{\partial l_j}$.

Next, to analyze how the cutoffs vary with firm age analytically, we can use the first-order stochastic dominance of the posterior distribution across different firm ages.[83] Given (1) and the log normality assumption, there is a point $\hat{P} \equiv \frac{\bar{\nu}^{old}\sigma^{young} - \bar{\nu}^{young}\sigma^{old}}{\sigma^{young} - \sigma^{old}}$ for $\ln P$, with which the cumulative distribution functions F for the posteriors of young and old firms follow: $F^{old}(\ln P) \geq (\leq) F^{young}(\ln P)$ if $\ln P \geq (\leq) \hat{P}$.

Suppose the productivity cutoffs $\mathcal{P}^{h,q,l}$ are given as constant. Given $\frac{\partial \hat{P}}{\partial \tilde{P}} = \frac{\sigma^{young}\sigma^{old}(a^{old} - a^{young})}{\sigma^{young} - \sigma^{old}} > 0$, as $\tilde{P}$ increases, there will be a point after which the middle cutoff $\mathcal{P}^q$ (for worker quits) goes below $\hat{P}$. Let $\bar{\tilde{P}}^H$ denote this point of $\tilde{P}$. Conversely, as $\tilde{P}$ decreases, there will be another point after which the lower cutoff $\mathcal{P}^l$ (for layoffs) goes above $\hat{P}$, which is denoted by $\bar{\tilde{P}}^L$.[84] Given (D.33), the marginal value of a labor input increases in P (with the constant productivity cutoffs $\mathcal{P}^{h,q,l}$ assumed as before). Thus, the condition $\mathbb{E}_j^{old}[\frac{\partial V^{init}(a_j', \tilde{P}_j, l_j, P_j')}{\partial l_j}] \geq (\leq) \mathbb{E}_j^{young}[\frac{\partial V^{init}(a_j', \tilde{P}_j, l_j, P_j')}{\partial l_j}]$ holds if $\tilde{P}_j \geq \bar{\tilde{P}}^H$ ($\tilde{P}_j \leq \bar{\tilde{P}}^L$). This implies, from (D.22), (D.26), (D.27), that the productivity cutoffs need to differ between young and old firms. In particular,

[83] The exact productivity cutoffs can only be determined numerically as an endogenous function of firm state variables.

[84] The exact values of $\bar{\tilde{P}}^H$ and $\bar{\tilde{P}}^L$ can be determined numerically.

they are adjusted to be lower for older firms if $\tilde{P}_j \geq \bar{\tilde{P}}^H$ and for younger firms if $\tilde{P}_j \leq \bar{\tilde{P}}^L$.

E Wage Differentials: Baseline vs. Counterfactual

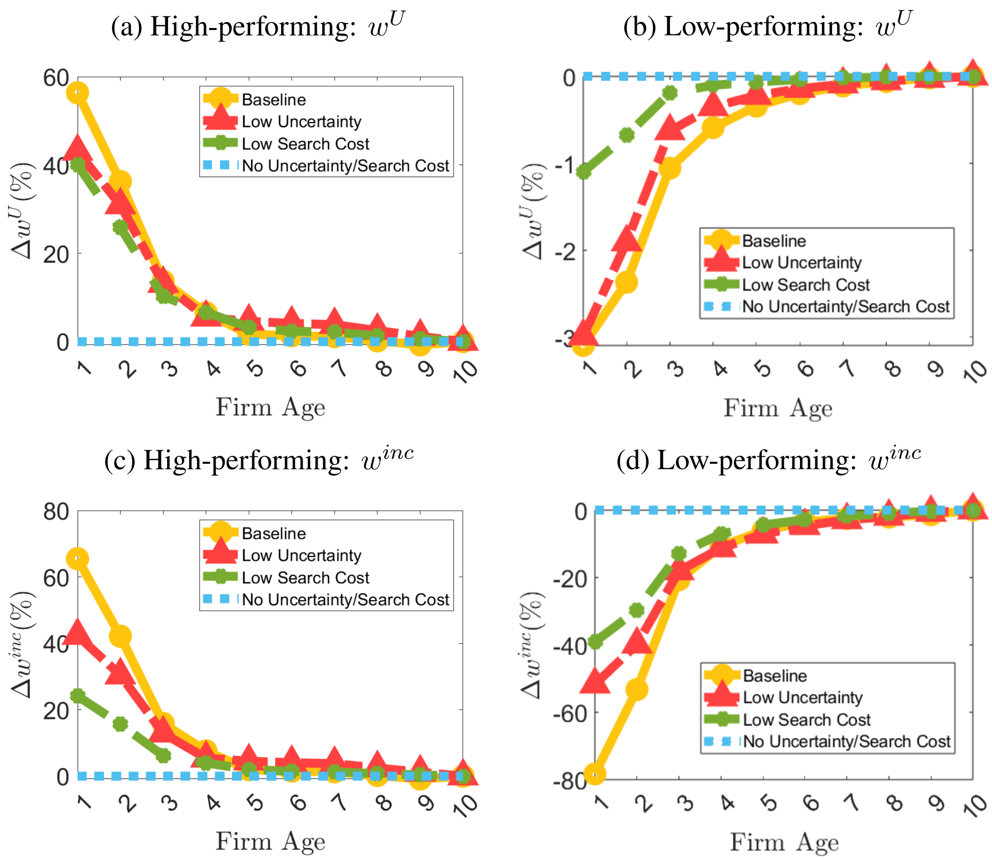

Figure E.1: Baseline vs. Counterfactual (Low Uncertainty, Search Cost)

Figure E.1 compares the wage differentials for young firms between the baseline economy and two counterfactual scenarios. It illustrates the wages of unemployed workers (top) and incumbent workers (bottom) at high-performing firms (left) and low-performing firms (right) with the same $(\tilde{P}_{j,-1}, l_{j,-1}, P_j)$ across different firm

[84] This figure shows wages for unemployed workers (top) and incumbent workers (bottom) at high-performing firms (left) and low-performing firms (right) with the same $(\tilde{P}_{j,-1}, P_j, l_{j,-1})$ across different ages in the counterfactual economy, under conditions of low uncertainty (red), low search friction (green), and no uncertainty or search friction (blue). Wage differentials are presented as percentage differences relative to those paid by the oldest firm (age 10).

ages in the counterfactual economy. The analysis is conducted under three conditions: low uncertainty (red), low search frictions (green), and no uncertainty or search frictions (blue). Wage differentials are expressed as percentage differences relative to those paid by the oldest firms (age 10) in this figure.

Consistent with the main findings, wage differentials are reduced in both counterfactuals with either lower uncertainty or search frictions. Note that if there is no uncertainty or no search friction, the wage differentials across firm age become zero.

F Data Appendix

F.1 Longitudinal Business Database (LBD)

The LBD tracks the universe of U.S. business establishments and firms that have at least one paid employee, annually from 1976 onward. Establishments that are owned by a parent firm are grouped under a common firm identifier, which allows me to aggregate establishment-level activities to the firm level. The LBD contains basic information such as employment, payroll, revenue, NAICS codes, employer identification numbers, business name, and location, which enables me to measure firm size, age, entry, exit, productivity, and employment growth.[85]

F.1.1 Longitudinal Firm Identifiers

One limitation of the LBD is the lack of longitudinally consistent firm identifiers.[86] However, longitudinal consistency of firm identifiers is necessary for my analysis to track firms' history of performance as well as to estimate noise components in firm type learning process. Therefore, I construct and use longitudinal firm identifiers following Dent et al. (2018). Henceforth, I will use the term "firm identifier" to refer to the longitudinal firm identifiers constructed using this method.

F.2 Longitudinal Employer Household Dynamics (LEHD)

The LEHD is constructed from quarterly Unemployment Insurance (UI) system wage reports of states participating in the program, which collect quarterly earnings

[85] Jarmin and Miranda (2002), Haltiwanger et al. (2016), and Chow et al. (2021) contain more detailed information about the LBD. Fort and Klimek (2018) construct time-consistent NAICS codes for LBD establishments after the implementation of a change from the SIC to NAICS in 1997.

[86] Although the redesigned LBD has a new firm identifier that links firms across time by correcting previous firm identifiers that are recycled in the old LBD, it is still not yet a true longitudinal identifier and has not yet resolved firm reorganization issues. See more discussion in Chow et al. (2021).

and employment information, along with demographic information.[87] The data cover over 95 percent of private sector workers, and the length of time series varies across states covered by the LEHD. I have access to 29 states covering over 60 percent of U.S. private sector employment.[88] The data enable me to identify worker heterogeneity, employment history, and job mobility. Linking the LEHD to the LBD with a crosswalk between employer identification numbers (EINs) and state-level employer identification numbers (SEINs), I track employer information for each job. The UI data, the main source of the LEHD, assign firms a state-level employer identification number (SEIN) that captures the activity of a firm within a state.

F.2.1 Main Jobs

The LEHD defines a job as the presence of an individual-employer match, with earnings defined as the amount earned from that job during the quarter. However, it does not record the start and end dates of a job, which makes the total number of weeks during that quarter unknown. To avoid potential bias from this, I follow the literature and restrict my analysis to 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. 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.

[87] The earnings data in the LEHD are reported on a quarterly basis, which include all forms of compensation that are taxable.

[88] 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.

F.2.2 Previous Employment Status

Following Haltiwanger et al. (2018), I can identify workers' previous job using a within/adjacent quarter approach, which allows for a brief nonemployment period between workers' last day on the previous job and their first day on the contemporaneous job. Therefore, workers are identified as previously employed if they had at least one full-quarter job within the most recent three quarters before t, and as non-employed if they had no full-quarter jobs within those three quarters.

Note that restricting the sample to full-quarter main jobs makes use of the three-quarter duration to define previous jobs. For notational convenience, let $(t - q1)$ denote the quarter prior to t, and $(t - q2)$ denote two quarters prior to t, and so on. If a worker had any full-quarter jobs at either $(t - q1)$ or $(t - q2)$, this implies that the worker must have moved to the contemporaneous job within quarter $(t - q1)$. The latter could happen if the worker had some overlapping period between $(t - q1)$ and t in job transition. If a worker had any full-quarter jobs at $(t - q3)$, this means that the worker must have left the job at $(t - q2)$, had a brief nonemployment period between $(t - q2)$ and $(t - q1)$, and joined the contemporaneous job at $(t - q1)$. Alternatively, the within quarter approach identifies workers as previously employed if they had at least one full-quarter job within the latest two quarters before t, where the previous job is defined by the most recent main full-quarter job within the most recent two quarters before t.

In the LEHD, I identify workers who had no employment in any states during the previous period, i.e., those who had no earnings from any states in any of the three most recent quarters before time t, as unemployed. For this group, I set their previous employer fixed effect to zero and introduce a dummy variable indicating their non-employment status. Additionally, for workers employed in states beyond the scope of my data in the previous period, where I lack information about their previous employer and earnings, I set the previous employer fixed effect to zero and include a dummy variable for their employment status.

F.3 Summary Statistics

Table F1: Summary Statistics

A. Worker-year Sample	Mean (sd)	B. Firm-year Sample	Mean (sd)
Worker Age	40.05	Firm Size	10.42
	(14.67)		(50.2)
Earnings (2009$)	9,670	Firm Age	5.492
	(27,830)		(3.347)
Earnings (log, 2009$)	8.697	Revenue (thousands, 2009$)	1,633
	(1.027)		(7,736)
Job Tenure (years)	3.66	Revenue Prod. (log, 2009$)	4.764
	(2.6)		(1.041)
Education	2.68	Employment Growth	0.0174
	(1.025)		(0.382)
Observations	50,170,000	Observations	6,959,000

Note: The table presents summary statistics for the main regression samples. Panel A displays statistics for the worker-year level sample, while Panel B presents statistics for the firm-year level sample. The first row of each variable indicates the mean, and the second row (in brackets) displays the standard deviation. Jobs are defined by the full-quarter main job in the first quarter of each year. Education categorizes workers based on their highest level of education attainment (1 - Less than high school, 2 - High school, 3 - Some college, 4 - Bachelor's degree or higher). All nominal variables are adjusted to 2009 dollars. Observation counts are rounded to the nearest 10,000 to avoid potential disclosure risks.

G Full Tables

Table G2: 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)
High performing	0.002	0.002
	(0.001)	(0.001)
Average Firm Prod. (up to $t-1$)	0.009***	0.012***
	(0.001)	(0.001)
Current Prod. (at t)	0.020***	0.015***
	(0.001)	(0.001)
Firm Size (at t)	0.017***	
	(0.001)	
Firm Size (at $t-1$)		0.013***
		(0.001)
Previous Employer (AKM)	0.267***	0.270***
	(0.001)	(0.001)
Observations	50,170,000	50,170,000
Fixed effects	g, s	g, s
Controls	Full (current size)	Full (lagged size)

Note: The table reports the full results for the main earnings regression. 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 (g), state (s) fixed effects, the coefficient of the indicator for worker's previous non-employment status are suppressed. Observations are unweighted.

Table G3: The Effect of Uncertainty on Young Firms' Wage Differentials

	Earnings Residuals	Earnings Residuals
Young	-0.001	-0.001
	(0.001)	(0.001)
$\times$ Uncertainty (at t)	-0.004	-0.004
	(0.002)	(0.002)
Young $\times$ High performing	0.012***	0.012***
	(0.002)	(0.002)
$\times$ Uncertainty (at t)	0.006***	0.006***
	(0.002)	(0.002)
High performing	-0.022***	-0.022***
	(0.001)	(0.001)
Uncertainty	-0.033***	-0.033***
	(0.001)	(0.001)
Uncertainty $\times$ High performing	0.028***	0.028***
	(0.001)	(0.001)
Average Firm Prod. (up to $t-1$)	0.009***	0.011***
	(0.000)	(0.000)
Current Prod. (at t)	0.020***	0.016***
	(0.000)	(0.000)
Firm Size (at t)	0.012***	
	(0.000)	
Firm Size (at $t-1$)		0.010***
		(0.000)
Previous Employer (AKM)	0.269***	0.271***
	(0.000)	(0.000)
Observations	50,170,000	50,170,000
Fixed effects	g, s	g, s
Controls	Full (current size)	Full (lagged size)

Note: The table reports the full results for the earnings regression interacted with industry-level uncertainty. The set of controls and fixed effects remain the same as in the baseline Table G2. Each column uses either current or lagged firm size. 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.

H Robustness Test for the Baseline Regression

Table H4: Wage Differentials for Young Firms (excluding firm size)

	Earnings Residuals	Earnings Residuals
Young	-0.006***	-0.007***
	(0.001)	(0.001)
Young $\times$ High performing	0.013***	0.015***
	(0.001)	(0.001)
High performing	0.005***	0.004***
	(0.001)	(0.001)
Average Firm Prod. (up to $t-1$)	0.016***	0.006***
	(0.001)	(0.001)
Current Prod. (at t)		0.015***
		(0.001)
Previous Employer (AKM)	0.283***	0.281***
	(0.001)	(0.001)
Observations	50,170,000	50,170,000
Fixed effects	g, s	g, s

Note: The table reports the earnings regression results. Firm controls include past-average productivity and current productivity (but not log employment size). Controls associated with worker's previous employment status are 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 (g), state (s) fixed effects, the coefficient of the indicator for worker's previous non-employment status are suppressed. Observations are unweighted.

Table H5: Wage Differentials for Young Firms (propensity score weighted)

	Earnings Residuals	Earnings Residuals	Earnings Residuals	Earnings Residuals
Young	-0.007***	-0.008***	-0.003***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Young $\times$ High performing	0.015***	0.018***	0.019***	0.019***
	(0.001)	(0.001)	(0.001)	(0.001)
High performing	0.004***	0.002*	-0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Avg. Firm Prod (up to $t-1$)	0.017***	0.003***	0.005***	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)
Current Prod. (at t)		0.021***	0.027***	0.021***
		(0.001)	(0.001)	(0.001)
Firm Size			0.020***	
			(0.000)	
Firm Size (at $t-1$)				0.015***
				(0.000)
Previous Employer (AKM)	0.281***	0.278***	0.266***	0.269***
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	50,170,000	50,170,000	50,170,000	50,170,000
Fixed effects	g, s	g, s	g, s	g, s

Note: The table reports results for regression of earning residuals on young firm and High performing indicators. Firm controls include past-average productivity level, current productivity level, and log employment size. Controls associated with worker's previous employment status are 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 weighted with inverse propensity score weights of author's own construction.

Table H6: Wage Differentials for Young Firms (bootstrapped standard errors)

	Earnings Residuals	Earnings Residuals	Earnings Residuals
Young	-0.006***	-0.007***	-0.002***
	(0.001)	(0.001)	(0.001)
Young $\times$ High performing	0.013***	0.015***	0.015***
	(0.002)	(0.002)	(0.002)
High performing	0.005***	0.004*	0.002
	(0.002)	(0.002)	(0.002)
Average Firm Prod. (up to $t-1$)	0.016***	0.006***	0.009***
	(0.000)	(0.001)	(0.001)
Current Prod. (at t)		0.015***	0.020***
		(0.001)	(0.001)
Firm Size			0.017***
			(0.000)
Previous Employer (AKM)	0.283***	0.281***	0.267***
	(0.001)	(0.001)	(0.001)
Observations	50,170,000	50,170,000	50,170,000
Fixed effects	g, s	g, s	g, s

Note: The table reports the 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. Note that the only difference from the main table is the standard errors. Observation counts are rounded to the nearest 10,000 to avoid potential disclosure risks. Estimates for constant, industry (g), state (s) fixed effects, the coefficient of the indicator for worker's previous non-employment status are suppressed. Observations are unweighted.

Table H7: Wage Differentials for Young Firms (with previous earnings)

	(1) Earnings Residuals	(2) Earnings Residuals	(3) Earnings Residuals	(4) Earnings Residuals	(5) Earnings Residuals	(6) Earnings Residuals	(7) Earnings Residuals
Young	-0.003***	-0.003***	-0.004***	-0.005***	-0.005***	-0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Young × High performing	0.014***	0.014***	0.016***	0.018***	0.018***	0.019***	0.019***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
High performing	0.001***	0.001***	-0.004	-0.010***	-0.010***	-0.012***	-0.012***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Average Prod. (up to $t-1$)	0.006***	0.003***	0.006***	-0.009***	-0.007***	-0.005***	-0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Current Prod. (at t)		0.005***	0.012***		-0.003***	0.003***	0.000
		(0.001)	(0.001)		(0.001)	(0.001)	(0.001)
Firm Size (at t)			0.028***			0.018***	
			(0.001)			(0.000)	
Firm Size (at $t-1$)							0.014***
							(0.000)
Previous Employer (AKM)				0.155***	0.155***	0.141***	0.160***
				(0.001)	(0.001)	(0.001)	(0.001)
Previous Earnings	0.194***	0.194***	0.190***	0.167***	0.167***	0.167***	0.165***
	(0.001)	(0.001)	(0.001)	(0.001)	(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	50,170,000
Fixed effects	g, s	g, s	g, s	g, s	g, s	g, s	g, s

Note: The table reports the earnings regression results. Firm controls include past-average productivity, current productivity, and log employment size. Controls associated with worker's previous employment status are previous earning level (in all columns) along with AKM firm fixed effect associated with the previous employer (in the last four columns) 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.

Table H8: Wage Differentials for Young Firms (worker skill controlled)

	Earnings Residuals	Earnings Residuals	Earnings Residuals
Young	-0.008***	-0.009***	-0.004***
	(0.001)	(0.001)	(0.001)
Young $\times$ High performing	0.016***	0.017***	0.017***
	(0.001)	(0.001)	(0.001)
High performing	0.004***	0.002*	0.002
	(0.001)	(0.001)	(0.001)
Average Firm Prod. (up to $t-1$)	0.015***	0.005***	0.008***
	(0.001)	(0.001)	(0.001)
Current Prod. (at t)		0.014***	0.020***
		(0.001)	(0.001)
Firm Size			0.017
			(0.000)
Previous Employer (AKM)	0.281***	0.279***	0.265***
	(0.001)	(0.001)	(0.001)
Observations	50,170,000	50,170,000	50,170,000
Fixed effects	g, s	g, s	g, s

Note: The table reports the earnings regression results. Firm controls include past-average productivity, current productivity, and log employment size. Controls associated with worker's previous employment status are AKM firm fixed effect associated with the previous employer and a dummy for non-employed workers in the previous period. Note that the only difference from the main table is the earnings residuals, which are computed after additionally controlling for worker skills in the first stage. Observation counts are rounded to the nearest 10,000 to avoid potential disclosure risks. Estimates for constant, industry (g), state (s) fixed effects, the coefficient of the indicator for worker's previous non-employment status are suppressed. Observations are unweighted.

Table H9: Wage Differentials for Young Firms (with young firm risks)

	Earnings Residuals	Earnings Residuals	Earnings Residuals
Young	-0.006***	-0.006***	-0.003***
	(0.001)	(0.001)	(0.001)
Young $\times$ High performing	0.013***	0.015***	0.015***
	(0.001)	(0.001)	(0.001)
High performing	0.005***	0.004***	0.002
	(0.001)	(0.001)	(0.001)
Average Firm Prod. (up to $t-1$)	0.016***	0.006***	0.009***
	(0.001)	(0.001)	(0.001)
Firm Prod. (at t)		0.015***	0.020***
		(0.001)	(0.001)
Firm Size			0.017***
			(0.000)
Previous Employer (AKM)	0.283***	0.281***	0.267***
	(0.001)	(0.001)	(0.001)
Young Firm Risks	-0.009	-0.005	0.005
	(0.002)	(0.002)	(0.002)
Observations	50,170,000	50,170,000	50,170,000
Fixed effects	g, s	g, s	g, s

Note: The table reports the earnings regression results. Firm controls include past-average productivity, current productivity, and log employment size. Controls associated with worker's previous employment status are AKM firm fixed effect associated with the previous employer and a dummy for non-employed workers in the previous period. In addition, the dispersion of productivity shocks for young firms is included to control for the level of unobserved risks associated with them. Observation counts are rounded to the nearest 10,000 to avoid potential disclosure risks. Estimates for constant, industry (g), state (s) fixed effects, the coefficient of the indicator for worker's previous non-employment status are suppressed. Observations are unweighted.

Table H10: Wage Differentials for Young Firms (firm-level previous employment)

	Earnings Residuals	Earnings Residuals	Earnings Residuals
Young	-0.004***	-0.005***	-0.000
	(0.001)	(0.001)	(0.001)
Young $\times$ High performing	0.013***	0.014***	0.015***
	(0.001)	(0.001)	(0.001)
High performing	0.007***	0.006***	0.003**
	(0.001)	(0.001)	(0.001)
Average Firm Prod. (up to $t-1$)	0.022***	0.010***	0.013***
	(0.001)	(0.001)	(0.001)
Firm Prod. (at t)		0.017***	0.023***
		(0.001)	(0.001)
Firm Size			0.020***
			(0.000)
Previous Employer (AKM)	0.281***	0.279***	0.264***
	(0.001)	(0.001)	(0.001)
Observations	50,170,000	50,170,000	50,170,000
Fixed effects	g, s	g, s	g, s

Note: The table reports the earnings regression results. Firm controls include past-average productivity, current productivity, and log employment size. Controls associated with worker's previous employment status are AKM firm fixed effect associated with the previous employer (estimated at the firm level, rather than the SEIN level) 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 (g), state (s) fixed effects, the coefficient of the indicator for worker's previous non-employment status are suppressed. Observations are unweighted.

Table H11: Wage Differentials for Young Firms (firm-level regression)

	Earnings Residuals	Earnings Residuals	Earnings Residuals	Earnings Residuals
Young	-0.010***	-0.010***	-0.010***	-0.010***
	(0.001)	(0.001)	(0.001)	(0.001)
Young $\times$ High performing	0.016***	0.017***	0.019***	0.020***
	(0.001)	(0.001)	(0.001)	(0.001)
High performing	0.018***	0.018***	0.016***	0.017***
	(0.001)	(0.001)	(0.001)	(0.001)
Average Firm Prod. (up to $t-1$)	0.033***	0.049***	0.029***	0.043***
	(0.001)	(0.001)	(0.001)	(0.001)
Current Prod. (at t)	0.072***	0.055***	0.0746***	0.0586***
	(0.001)	(0.001)	(0.001)	(0.001)
Firm Size (at t)	0.067***		0.067***	
	(0.000)		(0.001)	
Firm Size (at $t-1$)		0.0576***		0.0562***
		(0.000)		(0.001)
Observations	6,959,000	6,959,000	6,959,000	6,959,000
Fixed effects	g, s	g, s	g, s	g, s
Weighted	No	No	Yes	Yes

Note: The table reports the firm-level earnings regression results. The dependent variable is the average earnings residuals across workers within each firm. As before, firm-level characteristics are controlled, including past-average productivity, current productivity, and log employment size. Observation counts are rounded to the nearest 10,000 to avoid potential disclosure risks. Estimates for constant, industry (g), state (s) fixed effects. Observations are unweighted in the first two columns, and are weighted by inverse propensity score weights in the last two columns.

Table H12: The Effect of Uncertainty on Young Firms' Wage Differentials (lagged value)

	Earnings Residuals	Earnings Residuals
Young	-0.001	-0.002
	(0.002)	(0.002)
$\times$ Uncertainty (at $t-1$)	-0.005**	-0.004*
	(0.002)	(0.002)
Young $\times$ High performing	0.003	0.005**
	(0.002)	(0.002)
$\times$ Uncertainty (at $t-1$)	0.016***	0.015***
	(0.003)	(0.003)
Observations	50,170,000	50,170,000
Fixed effects	g, s	g, s
Controls	Full (current size)	Full (lagged size)

Note: The table reports the earnings regression interacted with industry-level uncertainty (lagged value). The set of controls remains the same as in the baseline Table G2. The first column uses the current size, and the second column uses the lagged value. 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.

I Impact of Earnings Differentials on Firm Outcomes

In this section, I examine the relationship between earnings differentials and firm outcomes (hiring or employment growth) as follows:

$$Y_{jt} = \beta\hat{\epsilon}_{jt} + Z_{jt}\gamma + \mu_{g(j,t)} + \mu_{s(j,t)} + \alpha + \xi_{jt}, \tag{I.34}$$

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, size, and productivity), and $\mu_{g(j,t)}$ and $\mu_{s(j,t)}$ are industry and state fixed effects, respectively. The top panel (A) in Table I13 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. This supports interpreting earnings differentials as stemming from uncertain job prospects, ruling out other hypotheses such as performance pay or surplus sharing. The results are robust using $\hat{P}_{jt}$ estimated in (17) as shown in the bottom panel (B) of the table. Furthermore, the results are robust to applying inverse propensity score weights, as presented in the following Table I14.

Table I13: The Effect of Wage Differentials on Firm Outcomes

A. Productivity (P)	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)
Firm Productivity	0.588***	0.302***	0.092***	0.102***
	(0.033)	(0.035)	(0.000)	(0.000)
Firm Size	7.964***	6.230***	-0.040***	-0.048***
	(0.133)	(0.068)	(0.000)	(0.000)
Firm Age	0.039***	0.007	-0.001***	-0.001***
	(0.008)	(0.008)	(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

B. Productivity ($\hat{P}$)	Hire (firm)	Hire (SEIN)	ΔEmp (Δlog)	ΔEmp (DHS)
Earnings Residuals	-0.498***	-0.369***	-0.012***	-0.015***
	(0.020)	(0.024)	(0.000)	(0.000)
Average Firm Prod.	-0.904***	-0.845***	-0.095***	-0.108**
	(0.035)	(0.050)	(0.000)	(0.001)
Current Firm Prod.	1.31***	0.924***	0.176***	0.197***
	(0.039)	(0.044)	(0.000)	(0.001)
Firm Size	7.998***	6.259***	-0.035***	-0.043***
	(0.134)	(0.068)	(0.000)	(0.000)
Firm Age	0.042***	0.009	-0.001***	-0.001***
	(0.008)	(0.008)	(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	$\hat{P}$, $\tilde{P}$, size, age	$\hat{P}$, $\tilde{P}$, size, age	$\hat{P}$, $\tilde{P}$, size, age	$\hat{P}$, $\tilde{P}$, size, age

Note: The table reports the effect of earnings residuals on firm-level outcomes. Firm controls include firm productivity, log employment size, and age in the top panel (A), and the past-average productivity level ($\tilde{P}_{j,-1}$, up to $t-1$) and the current value (P_j, at t) of the estimated firm productivity ($\hat{P}_j$) is used for firm productivity in the bottom panel (B). New hires are either the firm-level total new hire (first column) or the average of the SEIN-level new hires (second column). Employment growth is either the log-difference (third column) or the DHS growth (last column) 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.

Table I14: The Effect of Wage Differentials on Firm Outcomes (propensity score weighted)

A. Productivity (P)	Hire (firm)	Hire (SEIN)	ΔEmp (Δlog)	ΔEmp (DHS)
Earnings Residuals	-0.285***	-0.275***	-0.016***	-0.019***
	(0.010)	(0.041)	(0.000)	(0.000)
Firm Prod.	0.370***	0.254***	0.086***	0.095***
	(0.014)	(0.030)	(0.000)	(0.000)
Firm Size	5.426***	4.839***	-0.055***	-0.064***
	(0.071)	(0.058)	(0.000)	(0.000)
Firm Age	0.009**	-0.014*	-0.001***	-0.001***
	(0.004)	(0.007)	(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

B. Productivity ($\hat{P}$)	Hire (firm)	Hire (SEIN)	ΔEmp (Δlog)	ΔEmp (DHS)
Earnings Residuals	-0.274***	-0.266***	-0.014***	-0.016***
	(0.010)	(0.042)	(0.000)	(0.000)
Average Prod.	-0.515***	-0.504***	-0.092***	-0.103***
	(0.022)	(0.052)	(0.001)	(0.001)
Current Prod.	0.793***	0.646***	0.168***	0.187***
	(0.021)	(0.043)	(0.001)	(0.001)
Firm Size	5.452***	4.864***	-0.049***	-0.058***
	(0.071)	(0.059)	(0.000)	(0.000)
Firm Age	0.009**	-0.014*	-0.001***	-0.001***
	(0.004)	(0.007)	(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	$\hat{P}$, $\tilde{P}$, size, age	$\hat{P}$, $\tilde{P}$, size, age	$\hat{P}$, $\tilde{P}$, size, age	$\hat{P}$, $\tilde{P}$, size, age

Note: All remains the same as in Table I13, except for the observations weighted with inverse propensity score weights of author's own construction.

Table J15: Aggregate Implications of Uncertainty (long run)

Industry FE	(1) Entry	(2) Young firm share	(3) HG young firm share	(4) HG young avg. growth	(5) Prod.
Uncertainty	-0.126***	-0.372***	-0.183***	-0.279***	-2.06***
	(0.020)	(0.071)	(0.026)	(0.046)	(0.288)
Observations	250	250	250	250	250
Fixed effects	g, t	g, t	g, t	g, t	g, t

Note: The table reports results from regressions of the long-run value (industry fixed effects) of firm entry, the share of young firms, and the share and growth of high-growth young firms, and aggregate productivity in each column. Each measure is regressed on the counterpart for uncertainty at the industry level. Observation counts are rounded to the nearest 50 to mitigate potential disclosure risks. Estimates for the constant term are suppressed. Observations are unweighted.

J Long-Run Relationship

I further examine the long-run relationship in the steady-state economy of the model by estimating the industry fixed effects of the variables, which proxy the steady-state level for each industry. I then run the following cross-sectional regression:

$$\hat{\delta}_g^Y \ = \ \beta\hat{\delta}_g^{Uncertainty} \ + \alpha + \ \epsilon_g, \tag{J.35}$$

where δ_g^Y and $\delta_g^{Uncertainty}$ represent the industry fixed effects of Y and uncertainty, respectively.[89]

The result is displayed in Table J15. This confirms a negative and statistically significant correlation between uncertainty and the aggregate variables, even in the long run.

[89]The industry fixed effects of a variable X are estimated as follows: $X_{gt} = \delta_g^X + \delta_t^X + \alpha^X + \varepsilon_{gt}^X$, with year fixed effects δ_t^X controlled.

References

Abowd, John M, Francis Kramarz, and David N Margolis, "High wage workers and high wage firms," *Econometrica*, 1999, *67* (2), 251–333.

Akcigit, Ufuk and Sina T Ates, "What happened to US business dynamism?," *Journal of Political Economy*, 2023, *131* (8), 2059–2124.

Babina, Tania, Wenting Ma, Christian Moser, Paige Ouimet, and Rebecca Zarutskie, "Pay, employment, and dynamics of young firms," *Kenan Institute of Private Enterprise Research Paper*, 2019, (19-25).

Bartelsman, Eric, John Haltiwanger, and Stefano Scarpetta, "Cross-Country Differences in Productivity: The Role of Allocation and Selection," *American Economic Review*, February 2013, *103* (1), 305–334.

Bilal, Adrien, Niklas Engbom, Simon Mongey, and Giovanni L Violante, "Firm and worker dynamics in a frictional labor market," *Econometrica*, 2022, *90* (4), 1425–1462.

Bloom, Nicholas, Fatih Guvenen, Benjamin S Smith, Jae Song, and Till von Wachter, "The disappearing large-firm wage premium," in "AEA Papers and Proceedings," Vol. 108 2018, pp. 317–22.

Blundell, Richard and Stephen Bond, "Initial conditions and moment restrictions in dynamic panel data models," *Journal of Econometrics*, 1998, *87* (1), 115–143.

Brown, Charles and James L Medoff, "Firm age and wages," *Journal of Labor Economics*, 2003, *21* (3), 677–697.

Burton, M Diane, Michael S Dahl, and Olav Sorenson, "Do start-ups pay less?," *ILR Review*, 2018, *71* (5), 1179–1200.

Card, David, Ana Rute Cardoso, Joerg Heining, and Patrick Kline, "Firms and labor market inequality: Evidence and some theory," *Journal of Labor Economics*, 2018, *36* (S1), S13–S70.

_ , Jörg Heining, and Patrick Kline, "Workplace heterogeneity and the rise of West German wage inequality," *The Quarterly Journal of Economics*, 2013, *128* (3), 967–1015.

Chow, Melissa C, Teresa C Fort, Christopher Goetz, Nathan Goldschlag, James Lawrence, Elisabeth Ruth Perlman, Martha Stinson, and T Kirk White, "Redesigning the Longitudinal Business Database," Technical Report, National Bureau of Economic Research 2021.

Coles, Melvyn G and Dale T Mortensen, "Equilibrium labor turnover, firm growth, and unemployment," *Econometrica*, 2016, *84* (1), 347–363.

Cooley, Thomas F and Vincenzo Quadrini, "Financial markets and firm dynamics," *American Economic Review*, 2001, *91* (5), 1286–1310.

Cooper, Russell, John Haltiwanger, and Jonathan L Willis, "Search frictions: Matching aggregate and establishment observations," *Journal of Monetary Economics*, 2007, *54*, 56–78.

de Melo, Rafael Lopes, "Firm wage differentials and labor market sorting: Reconciling theory and evidence," *Journal of Political Economy*, 2018, *126* (1), 313–346.

Decker, Ryan A, John Haltiwanger, Ron S Jarmin, and Javier Miranda, "Where has all the skewness gone? The decline in high-growth (young) firms in the US," *European Economic Review*, 2016, *86*, 4–23.

_ , _ , _ , and _ , "Changing business dynamism and productivity: Shocks versus responsiveness," *American Economic Review*, 2020, *110* (12), 3952–90.

Decker, Ryan, John Haltiwanger, Ron Jarmin, and Javier Miranda, "The role of entrepreneurship in US job creation and economic dynamism," *Journal of Economic Perspectives*, 2014, *28* (3), 3–24.

Dent, Robert C, Benjamin W Pugsley, Harrison Wheeler et al., "Longitudinal Linking of Enterprises in the LBD and SSL," Technical Report, Center for Economic Studies, US Census Bureau 2018.

Elsby, Michael WL and Axel Gottfries, "Firm dynamics, on-the-job search, and labor market fluctuations," *The Review of Economic Studies*, 2022, *89* (3), 1370–1419.

_ **and Ryan Michaels**, "Marginal jobs, heterogeneous firms, and unemployment flows," *American Economic Journal: Macroeconomics*, 2013, *5* (1), 1–48.

Fort, Teresa and Shawn Klimek, "The Effects of Industry Classification Changes on US Employment Composition," Technical Report, US Census Bureau, Center for Economic Studies 2018.

Foster, Lucia, Cheryl Grim, John C Haltiwanger, and Zoltan Wolf, "Innovation, productivity dispersion, and productivity growth," Technical Report, National Bureau of Economic Research 2018.

_ **, John Haltiwanger, and Chad Syverson**, "The slow growth of new plants: learning about demand?," *Economica*, 2016, *83* (329), 91–129.

Gouin-Bonenfant, Émilien, "Productivity Dispersion, Between-Firm Competition, and the Labor Share," *Econometrica*, 2022, *90* (6), 2755–2793.

Guimaraes, Paulo and Pedro Portugal, "A simple feasible procedure to fit models with high-dimensional fixed effects," *The Stata Journal*, 2010, *10* (4), 628–649.

Haltiwanger, John, "Job creation and firm dynamics in the United States," *Innovation Policy and the Economy*, 2012, *12* (1), 17–38.

Haltiwanger, John C, Henry R Hyatt, Lisa B Kahn, and Erika McEntarfer, "Cyclical job ladders by firm size and firm wage," *American Economic Journal: Macroeconomics*, 2018, *10* (2), 52–85.

Haltiwanger, John, Ron S Jarmin, and Javier Miranda, "Who creates jobs? Small versus large versus young," *Review of Economics and Statistics*, 2013, *95* (2), 347–361.

_ , _ , Robert Kulick, and Javier Miranda, "Data for: High growth young firms: contribution to job, output, and productivity growth," in "Measuring entrepreneurial businesses: current knowledge and challenges," University of Chicago Press. Access to this proprietary data was kindly provided by Javier Miranda., 2016, pp. 11–62.

_ , _ , _ , and _ , "1. High-Growth Young Firms," in "Measuring Entrepreneurial Businesses," University of Chicago Press, 2017, pp. 11–62.

Holtz-Eakin, Douglas, David Joulfaian, and Harvey S Rosen, "Sticking it out: Entrepreneurial survival and liquidity constraints," *Journal of Political Economy*, 1994, *102* (1), 53–75.

Jarmin, Ron S and Javier Miranda, "The longitudinal business database," *Available at SSRN 2128793*, 2002.

Jovanovic, Boyan, "Selection and the Evolution of Industry," *Econometrica*, 1982, pp. 649–670.

Kaas, Leo and Philipp Kircher, "Efficient firm dynamics in a frictional labor market," *American Economic Review*, 2015, *105* (10), 3030–60.

Kim, J Daniel, "Is there a startup wage premium? Evidence from MIT graduates," *Research Policy*, 2018, *47* (3), 637–649.

Menzio, Guido and Shouyong Shi, "Block recursive equilibria for stochastic models of search on the job," *Journal of Economic Theory*, 2010, *145* (4), 1453–1494.

— **and** — , "Efficient search on the job and the business cycle," *Journal of Political Economy*, 2011, *119* (3), 468–510.

Schaal, Edouard, "Uncertainty and unemployment," *Econometrica*, 2017, *85* (6), 1675–1721.

Song, Jae, David J Price, Fatih Guvenen, Nicholas Bloom, and Till Von Wachter, "Firming up inequality," *The Quarterly Journal of Economics*, 2019, *134* (1), 1–50.

Sorenson, Olav, Michael S Dahl, Rodrigo Canales, and M Diane Burton, "Do Startup Employees Earn More in the Long Run?," *Organization Science*, 2021.

Sterk, Vincent, Petr Sedláček, and Benjamin Pugsley, "The nature of firm growth," *American Economic Review*, 2021, *111* (2), 547–79.

U.S. Bureau of Labor Statistics, "Data: Unemployment Level, Thousands of Persons, Quarterly, Seasonally Adjusted-UNEMPLOY; Labor Force Flows Unemployed to Employed, Thousands of Persons, Quarterly, Seasonally Adjusted-LNS17100000," https://fred.stlouisfed.org/series/UNEMPLOY; https://fred.stlouisfed.org/series/LNS17100000 1998-2014. Accessed: Auguest 7, 2022.

— , "Data: Hires: Total Nonfarm (Rate), Quarterly (Average), Seasonally Adjusted-JTSHIR," https://fred.stlouisfed.org/series/JTSHIR 2001-2014. Accessed: Auguest 7, 2022.

U.S. Census Bureau, "Data: Business Dynamics Statistics Datasets, 4-digit NAICS by Firm Age, Annual," https://www.census.gov/data/datasets/

time-series/econ/bds/bds-datasets.html 1998-2014. Accessed: October 22, 2024.

—, "Data: Longitudinal Business Database, Annual; Longitudinal Employer-Household Dynamics, Quarterly (confidential data accessible in the Federal Statistical Research Data Center)," https://www.census.gov/programs-surveys/ces/data/restricted-use-data/longitudinal-business-database.html; https://www.census.gov/programs-surveys/ces/data/restricted-use-data/lehd-data.html 1998-2014. Accessed: January 23, 2024.

—, "Data: Job-to-Job Flow Counts, United States, all firms, all workers, Quarterly, Seasonally Adjusted," https://lehd.ces.census.gov/data/#j2j 2000-2014. Accessed: September 26, 2024.