

Workers' Job Prospects and Young Firm Dynamics

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Abstract

This paper investigates how worker beliefs and job prospects impact the wages and growth of young firms and quantifies aggregate implications. Building a heterogeneous-firm directed search model where workers gradually learn about firm types, I find that the learning creates endogenous wage differentials for young firms. High-performing young firms must pay a higher wage than that of equally high-performing old firms, while low-performing young firms offer a lower wage than that of equally low-performing old firms. Higher uncertainty amplifies the wage differentials and hampers firm entry and aggregate productivity. Using U.S. administrative employee-employer linked data, I provide consistent results.

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1 Introduction

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. and have been at the center of research.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. However, workers are less certain about young firm performance as an indicator of their fundamentals, due to the firms' lack of history. 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 not been much 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 build on the directed search model of [Schaal \(2017\)](#) and introduce symmetric learning as in [Jovanovic \(1982\)](#). A novel feature of the model

¹Using the Business Dynamics Statistics, I find that young firms (aged five or less) contribute to 29.76% of job creation, whereas their share of employment is only 12.73% in the U.S. during the period of 1998-2014. See also [Haltiwanger \(2012\)](#), [Haltiwanger et al. \(2013\)](#), [Decker et al. \(2014\)](#), [Decker et al. \(2016\)](#), [Haltiwanger et al. \(2016\)](#), and [Foster et al. \(2018\)](#).

is that workers need to learn about firms' underlying productivity types along the firm life cycle, 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 cumulative average performance above the cross-sectional prior mean, 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. Such wage differentials create a barrier at the hiring or retention margin of those young firms, increasing their marginal costs and hampering their growth. At the same time, young firms with low demonstrated potential, those with cumulative average performance below the cross-sectional prior mean, 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.

The model further allows me to quantify the macroeconomic implications of this job prospects channel for overall young firm activity and aggregate productivity. A counterfactual analysis suggests that an increase in the fundamental uncertainty regarding young firms' job prospects (or an increase in noise dispersion in the learning) can lead to declines in firm entry, the share of young firms, the growth of high potential young firms, as well as aggregate productivity. This is through the mechanism that higher uncertainty slows down the speed of learning about firm types, and increases gaps in workers' job prospects and the consequent wage differentials.

In particular, more uncertain prospects amplify the wage premia paid by high-performing young firms and hamper the growth of those young firms with high

potential. Furthermore, more uncertain prospects allow low-performing firms to pay less and linger in the economy. Thus, labor markets become tighter and overall hiring costs are raised for recruiting firms. This can in turn hamper overall allocative efficiency and decrease aggregate productivity. This shows that workers' job prospects at young firms can also have important macroeconomic impacts in the economy.

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 Unemployment Insurance (UI) systems in most U.S. states. Using the linked data, I estimate an individual-level earnings regression informed by the model. I find that controlling for worker heterogeneity and observable firm characteristics, i) young firms with high demonstrated potential (or high average productivity) pay more than their mature counterparts with the same observable characteristics, but ii) young firms with low demonstrated potential (or low average productivity) pay less relative to otherwise similar mature firms. This confirms the model's predictions about how learning and job prospects create wage differentials between young firms and their mature counterparts.

Moreover, I estimate the impact of the level of uncertainty on the earnings differentials of young firms by using industry-level variation in uncertainty (measured by the dispersion of firm-level productivity shocks) and interacting it with the earnings residuals. I find that the earnings differentials for young firms are more pronounced in industries with more dispersed firm-level productivity shocks. Lastly, I construct industry-level measures of business dynamism and examine their relationships with uncertainty. I find that higher uncertainty with more dispersed noise has a negative impact on overall business dynamism at the industry level. These findings are consistent with the model's aggregate implications.

Related Literature. This paper is related to several strands of literature. First, it contributes to a broad line of work in firm dynamics and macroeconomics that studies the post-entry dynamics and growth of young firms. Much previous research emphasizes the importance of financing constraints for entrepreneurship (Evans and Jovanovic, 1989; Holtz-Eakin et al., 1994; Cooley and Quadrini, 2001; Hurst and Lusardi, 2004; Kerr and Nanda, 2009; Robb and Robinson, 2014; Schmalz et al., 2017; Davis and Haltiwanger, 2019). Other studies including Foster et al. (2016) and Akcigit and Ates (2019) emphasize frictions related to customer base accumulation or knowledge spillovers as barriers to firm entry and the growth of young firms. This paper expands this literature by linking firm dynamics to labor market dynamics and identifying workers' job prospects as a novel source affecting firm entry and young firm growth.

Second, this paper is also relevant to a large set of literature that studies inter-firm wage differentials and dynamics (Abowd et al., 1999, 2002, 2004; 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; Haltiwanger et al., 2012; Burton et al., 2018; Sorenson et al., 2021; Kim, 2018; Babina et al., 2019). 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 workers' uncertain job prospects and finds new datafacts supporting this channel.

Lastly, this paper is grounded in the directed labor search literature (Menzio and Shi, 2010, 2011). In particular, my work is closely related to Kaas and Kircher

(2015) and [Schaal \(2017\)](#), who link directed search to standard firm dynamics models. This paper contributes to this literature by adding a firm-type learning process to the directed search framework in a tractable way. The model still obtains block recursivity with firm heterogeneity in age and size and on-the-job search. Also, the model generates endogenous wage differentials across different firm ages, even after controlling for firms' observable characteristics, and allows the quantification of their macroeconomic implications.

The remainder of this paper is structured as follows: Section 2 develops a heterogeneous firm directed search model that extends [Schaal \(2017\)](#) by introducing a firm-type learning process; Section 3 lays out the model's main implications and mechanisms; Section 4 describes the model calibration and counterfactual exercises; Section 5 uses the data and tests the model implications for wage differentials of young firms and aggregate outcomes; and Section 6 concludes.

2 Theoretical Model

This section presents a baseline framework, which builds on [Schaal \(2017\)](#) by introducing a firm-type learning process in [Jovanovic \(1982\)](#).

2.1 The Environment

The model is set in discrete time and consists of a continuum of heterogeneous firms with homogeneous workers within frictional labor markets. Symmetric information is assumed for both firms and workers. The mass of workers is normalized to one, while the mass of firms is pinned down endogenously with free entry. Both firms and workers are risk neutral and have the same discount rate β . Firms all produce an identical homogeneous good which is the numeraire.

2.2 Firm-type Learning Process

Firms are born with different productivity types ν that are time invariant and unobserved to both firms and workers. Among entrants, ν is normally distributed with mean $\bar{\nu}_0$ and standard deviation σ_0 . Entrants do not know their own ν , but know the cross-sectional distribution of their type, $\nu \sim N(\bar{\nu}_0, \sigma_0^2)$. Workers have the same information. Thus, both entrants and workers start with a belief $\nu \sim N(\bar{\nu}_0, \sigma_0^2)$ at age 0. The dispersion of firm type σ_0 indicates the signal level in the economy.²

Observed productivity for firm j at time t , P_{jt} , follows a log-normal process $P_{jt} = e^{\nu_j + \varepsilon_{jt}}$, where $\varepsilon_{jt} \sim N(0, \sigma_\varepsilon^2)$ is a firm-specific shock that is independent over time and across firms. The dispersion of firm-level shocks σ_ε indicates the degree of uncertainty in the economy.³

Let a_{jt} denote the age of firm j at period t and $\bar{\nu}_{jt-1}$ and σ_{jt-1}^2 denote the prior (or updated posterior) mean and variance about firm j 's type at the beginning of period t , respectively. Upon observing the productivity level P_{jt} , both the firm and workers update their posterior beliefs about firm type ν_j using Bayes' rule as follows:

$$\nu_j | P_{jt} \sim N(\bar{\nu}_{jt}, \sigma_{jt}^2), \quad (2.1)$$

where

$$\bar{\nu}_{jt} = \frac{\frac{\bar{\nu}_0}{\sigma_0^2} + \frac{\sum_{i=0}^{a_{jt}} \ln P_{jt-i}}{\sigma_\varepsilon^2}}{\frac{1}{\sigma_0^2} + (a_{jt} + 1) \frac{1}{\sigma_\varepsilon^2}} = \frac{\frac{\bar{\nu}_0}{\sigma_0^2} + (a_{jt+1}) \frac{\bar{P}_{jt}}{\sigma_\varepsilon^2}}{\frac{1}{\sigma_0^2} + (a_{jt+1}) \frac{1}{\sigma_\varepsilon^2}} \quad (2.2)$$

$$\sigma_{jt}^2 = \frac{1}{\frac{1}{\sigma_0^2} + (a_{jt+1}) \frac{1}{\sigma_\varepsilon^2}} \quad (2.3)$$

²The more dispersed the type distribution is, the more signal agents can gain from observing firm productivity realizations.

³Higher shock dispersion generates more noise in the learning process.

where $\tilde{P}_{jt} \equiv \frac{\sum_{i=0}^{a_{jt}} \ln P_{jt-i}}{(a_{jt+1})}$ is the cumulative average of log productivity up to t .⁴

Note that firm age and the 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. The posterior mean in (2.2) is a weighted sum of the initial prior mean and the average observed productivity, with weights determined by firm age. The mean increases in average productivity, where higher average productivity enhances prospects about firms. On the other hand, the posterior mean increases in firm age only if firm j 's average productivity is above the initial cross-sectional mean ($\tilde{P}_{jt-1} > \bar{\nu}_0$), while decreasing in firm age if a firm's average productivity is below the cross-sectional mean ($\tilde{P}_{jt-1} < \bar{\nu}_0$).⁵ The posterior variance in (2.3) decreases in firm age, and the posterior converges to a degenerate distribution centered at the true type ν_j as firm ages. Further details are available in Online Appendix B.

Figure 1 illustrates these properties, showing the posterior beliefs across different firm ages, for a given level of average productivity (the red dashed line). For expositional convenience, I will refer to firms as “high-performing” if their average productivity is above the cross-sectional prior mean ($\tilde{P}_{jt-1} > \bar{\nu}_0$) and “low-performing” if the opposite holds ($\tilde{P}_{jt-1} < \bar{\nu}_0$) throughout the paper.⁶

2.3 Labor Market

The labor market is frictional. Following Schaal (2017), search is directed on both the worker and firm sides. Firms announce contracts to hire and retain workers each period. Following the convention in a standard directed search framework, a sufficient statistic to define labor markets is the level of promised utility that each

⁴See Online Appendix B for more details on the Bayes' rule.

⁵In other words, a higher age implies a better (worse) inferred type for the former (latter) case.

⁶Note that in Bayesian learning, both firms and workers learn from observable performance to infer firms' fundamental types. Therefore, a firm's average observed productivity (\tilde{P}_{jt-1}) indicates their “potential” type in a given period t , which converges to the firm's time-invariant type ν_j in the long run.

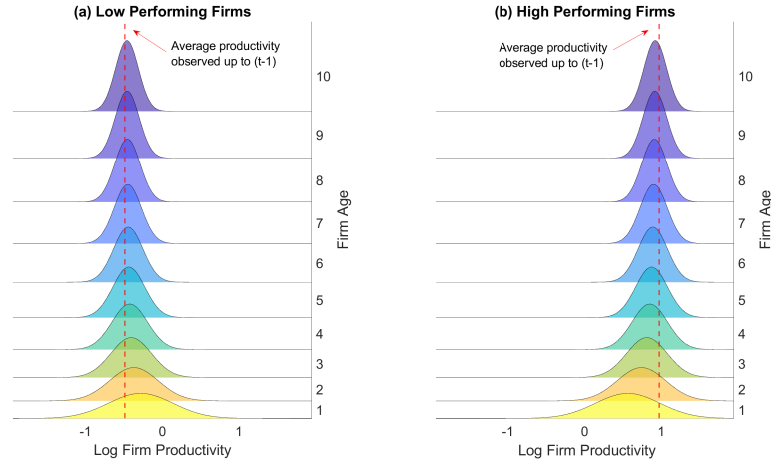


Figure 1: Posterior Distribution of Firm Type

contract delivers to workers upon matching.⁷ Thus, the labor market is a continuum of submarkets indexed by the total utility x_{jt} that firms (j) promise to workers.

Both firms and workers direct their search and choose a submarket to search in by taking into account a trade-off between the level of utility of a given contract and the corresponding matching probability. Matches are created within each market through a standard constant-returns-to-scale matching function. Firms post vacancies by paying a vacancy cost c .

Let $\theta(x)$ denote the market tightness (the vacancy-to-searchers ratio) in each submarket x .⁸ Let $f(\theta)$ and $q(\theta)$ be job finding and job filling rates for workers and firms, respectively.⁹ Firms and workers are assumed to visit one submarket at a time. There is both on-the-job and off-the-job search with the relative search efficiency λ for employed workers.

⁷This 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.

⁸Note that searchers in a given market x are either unemployed workers or employed workers who are searching for a new job while on their current job. More details can be found in Section 2.8.

⁹As is standard in the literature, I assume $f'(\theta) > 0$, $f(0) = 0$, $q'(\theta) < 0$, and $q(0) = 1$.

2.4 Dynamic Contracts

Contracts are written every period after matching occurs and before production takes place. Contracts are recursive and are assumed to be state-contingent and fully committed for firms.¹⁰ A contract for workers employed at firm j at t , Ω_{jt} , specifies the current wage w_{jt} , the next period's utility level \tilde{W}_{jt+1} , firm exit probability d_{jt+1} , and worker layoff probability s_{jt+1} , where the last three terms are contingent on the firm's next period state variables $(a_{jt+1}, \tilde{P}_{jt}, P_{jt+1}, l_{jt})$, where l_{jt} is the number of workers employed at firm j at the end of period t .

Thus, the contract can be written as

$$\Omega_{jt} = \{w_{jt}, d_{jt+1}, s_{jt+1}, \tilde{W}_{jt+1}\}, \quad (2.4)$$

where $d_{jt+1} \equiv d(a_{jt+1}, \tilde{P}_{jt}, P_{jt+1}, l_{jt})$, $s_{jt+1} \equiv s(a_{jt+1}, \tilde{P}_{jt}, P_{jt+1}, l_{jt})$, and $\tilde{W}_{jt+1} \equiv \tilde{W}(a_{jt+1}, \tilde{P}_{jt}, P_{jt+1}, l_{jt})$. Firms offer common contracts across workers with the same ex-post heterogeneity (the employment status of workers).¹¹ Since each firm is committed to its contracts, 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 . Since the model is solved at the steady state in a recursive form, I drop time subscripts onward.¹²

Figure 2 outlines the timeline. Incumbent and new firms enter with the beginning-of-period priors, employment size $l_{j,-1}$ and the contract $\Omega_{j,-1}$ announced in the

¹⁰Contracts are not committed for workers, which is the only distinction from Schaal (2017).

¹¹This means firms offer the same state-contingent next-period variables to workers as workers obtain the same ex-post heterogeneity once they join the firm in the current period. However, the current wage can vary across workers depending on the workers' previous employment status before joining the firm or being retained by the firm in a given period. Note that there is neither worker ex-ante heterogeneity nor human capital accumulated within a firm.

¹²Superscript t is used to denote next period variables at $t + 1$, and subscript -1 is used for the previous period variables at $t - 1$.

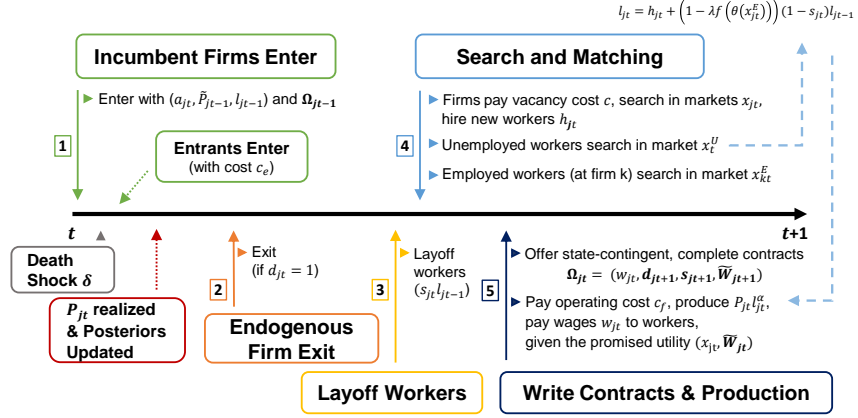


Figure 2: Timeline of the model

previous period.¹³ Next, a fraction δ of firms exit exogenously with a death shock. New firms enter afterwards by paying an entry cost c_e , where free entry is assumed. Firm productivity P_j is realized, after which firms decide whether to exit or stay, following the rule d_j , or whether to lay off workers with probability s_j . Both d_j and s_j are a function of the firm state variables $(a_j, \tilde{P}_{j,-1}, l_{j,-1}, P_j)$.

2.5 Model Timeline

Search and matching follows, with new and surviving incumbent firms on one side and unemployed and employed workers on the other side. Firms choose and search in market x_j , post vacancies v_j by paying the per-vacancy cost c , and hire new workers h_j with a job filling rate determined by market tightness $q(\theta(x))$.¹⁴ On the other hand, unemployed workers choose their market to search in x^U , and employed workers at firm j choose search market x_j^E . Unemployed and employed workers

¹³The priors depend on firm age and the average log productivity $(a_j, \tilde{P}_{j,-1})$. The beginning-of-period priors for incumbents are the posteriors updated by the end of the previous period.

¹⁴Here, the number of vacancies and new hires have the relationship $h_j = q(\theta(x_j))v_j$, and the vacancy cost per hire is $\frac{c}{q(\theta(x_j))}$.

find a job with probability $f(\theta(x^U))$ and $f(\theta(x_j^E))$, respectively. At the end of this process, firms will end up with employment level as the sum of new hires and the remaining incumbent workers after the departure of those laid off and those moving to other jobs ($l_j = h_j + (1 - \lambda f(\theta(x_j^E)))(1 - s_j)l_{j,-1}$).

Finally, firms enter the last stage in a given period, in which they write contracts to new and retained workers, and produce. They offer the workers the contract Ω_j as in (2.4). When writing this contract, firms are committed to providing utility \tilde{W}_j to surviving incumbent workers and x to new hires. Lastly, firms pay a fixed operating cost c_f , produce, and pay wages w_j to workers as announced in the contract Ω_j .

2.6 Workers' Problem

Unemployed Workers. Unemployed workers have the following value function U :

$$U = b + \beta \mathbb{E} \left[\max_{x^{U'}} (1 - f(\theta(x^{U'}))) U' + f(\theta(x^{U'})) x^{U'} \right], \quad (2.5)$$

where b is unemployment insurance and $x^{U'}$ is a market they search in, considering a trade-off between the promised utility $x^{U'}$ and the job finding probability f as a function of labor market tightness $\theta(x^{U'})$. Workers do not save and are risk neutral.

Employed Workers. Employed workers at firm j under the contingent contract Ω_j have the following value function after the search and matching process is complete:

$$\begin{aligned} \mathbf{W}(a_j, \tilde{P}_{j,-1}, l_{j,-1}, P_j, \Omega_j) = & w_j + \beta \mathbb{E}_j \left[\left(\delta + (1 - \delta)(\mathbf{d}'_j + (1 - \mathbf{d}'_j)\mathbf{s}'_j) \right) U' \right. \\ & \left. + (1 - \delta)(1 - \mathbf{d}'_j)(1 - \mathbf{s}'_j) \max_{x_j^{E'}} \left(\lambda f(\theta(x_j^{E'})) x_j^{E'} + (1 - \lambda f(\theta(x_j^{E'}))) \tilde{W}'_j \right) \right]. \end{aligned} \quad (2.6)$$

This shows that the workers first receive the wage w_j as specified in their con-

tracts.^{15, 16} 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 $\lambda f(\theta(x_j^{E'}))$, or (iii) they stay in the firm. In the case of firm exit or layoff, workers go to unemployment and get the value U' .¹⁷ $\mathbb{E}_j(\cdot)$ is the workers' expectation of P'_j based on their updated beliefs on ν_j , which characterizes the expected value across the three cases.

2.7 Firms' Problem

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

$$\begin{aligned} \mathbf{J}(a_j, \tilde{P}_{j,-1}, l_{j,-1}, P_j, \{\Omega_{j,-1}(i)\}_{i \in [0, l_{j,-1}]}) &= \max_{\substack{\{\Omega_j(i)\}_{i \in [0, l_j]}, \\ h_j, x_j}} P_j l_j^\alpha - \int_0^{l_j} w_j(i) di - c_f \\ &- \frac{c}{q(\theta(x_j))} h_j + \beta(1 - \delta) \mathbb{E}_j \left[(1 - d'_j) \mathbf{J}(a'_j, \tilde{P}_j, l_j, P'_j, \{\Omega_j(i)\}_{i \in [0, l_j]}) \right] \end{aligned} \quad (2.7)$$

at the search and matching stage in period t , subject to the following constraints:

$$l_j = h_j + (1 - s_j)(1 - \lambda f(\theta(x_j^E))) l_{j,-1} \quad (2.8)$$

$$\lambda f(\theta(x_j^{E'})) x_j^{E'} + (1 - \lambda f(\theta(x_j^{E'}))) \tilde{\mathbf{W}}'_j \geq U' \quad (2.9)$$

$$x_j^{E'} = \mathbf{x}^E(\tilde{\mathbf{W}}'_j) = \operatorname{argmax}_x f(\theta(x))(x - \tilde{\mathbf{W}}'_j) \quad (2.10)$$

$$\mathbf{W}(a_j, \tilde{P}_{j,-1}, l_{j,-1}, P_j, \Omega_j(i)) \geq x_j \quad \text{for new hires } i \in [0, h_j] \quad (2.11)$$

¹⁵The 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 $\tilde{P}_{j,t}$ (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.

¹⁶The contract $\Omega_j = \{w_j, d'_j, s'_j, \tilde{\mathbf{W}}'_j\}$ depends on the firm j 's state variable $(a_j, \tilde{P}_{j,-1}, l_{j,t-1}, P_j)$. The value function also depends on Ω_j as the contract can vary between new hires and incumbents.

¹⁷Layoffs are i.i.d. across incumbent workers.

$$\mathbf{W}(a_j, \tilde{P}_{j,-1}, l_{j,-1}, P_j, \Omega_j(i)) \geq \tilde{\mathbf{W}}_j \quad \text{for incumbent workers } i \in [h_j, l_j], \quad (2.12)$$

where the firm produces with labor using the decreasing returns-to-scale technology ($\alpha < 1$), $w_j(i)$ refers to the wage paid to worker $i \in [0, l_j]$ as a component of the contract $\Omega_j(\mathbf{i}) = \{w_j(i), \mathbf{d}'_j, \mathbf{s}'_j, \tilde{\mathbf{W}}'_j\}$, h_j is the new hires by firm j , x_j is the market firm j searches in, and $q(\theta(x_j))$ is the job filling probability within the market.¹⁸

Note that (2.8) is the employment law of motion, (2.9) is a participation constraint, which prevents workers' return to unemployment unless separations take place, and (2.10) is an incentive constraint based on incumbent workers' optimal on-the-job search. The firm takes into account their workers' incentive to move to other firms and internalizes the impact of their utility promises on workers' on-the-job search behavior.¹⁹ In addition, (2.11) and (2.12) are promise-keeping constraints for new hires and surviving incumbent workers (from the previous period), respectively.²⁰

After search and matching is complete, the firm enjoys an instantaneous profit equal to revenue $P_j l_j^\alpha$ minus the sum of the wage bill to its workers $\int_0^{l_j} w_j(i) di$, the operating fixed cost c_f , and the vacancy cost $\frac{c}{q(\theta(x_j))} h_j$, as specified in the first line in (2.7). In the following period, conditional on surviving the exogenous death shock with probability $(1 - \delta)$ and the state-contingent decision rule $\mathbf{d}'_j = 0$, the firm enters the search and matching process again and obtains the next period value.

Entrants. New firms enter each period by paying entry cost c_e after the death

¹⁸ $\Omega_j(\mathbf{i})$ only differs between new hires and incumbent workers (or between new hires depending on their origin). Firms offer the same contract to incumbent workers as there is no worker heterogeneity.

¹⁹Firms' choice of promised utility to remaining incumbent workers $\tilde{\mathbf{W}}_{jt+1}$ determines incumbent workers' choice of submarket for on-the-job search x_{jt+1}^E by the incentive condition, and firms take into account this when choosing $\tilde{\mathbf{W}}_{jt+1}$. Therefore, the number of workers who quit upon successful on-the-job search, $\lambda f(\theta(x_{jt}^E)) l_{jt-1}$, is predetermined by the state-contingent utility level $\tilde{\mathbf{W}}_{jt}$ that the firm announced in the preceding period and is committed to in the current period.

²⁰Because of the commitment assumption, the firm needs to announce contracts that deliver at least x_j and $\tilde{\mathbf{W}}_j$ to their newly hired and incumbent workers, respectively.

shock hits incumbent firms, but before the entrants' initial productivity is realized. Entrants have initial beliefs about their types with the cross-sectional mean $\bar{\nu}_0$ and standard deviation σ_0 , based on which they calculate the expected value from entry. They keep entering until the expected value equals the entry cost. After entering and observing their initial productivity, new firms decide whether to exit or stay. In the latter case, they search by paying c for each vacancy they post, hire workers with probability $q(\theta(x^e))$ in the market x^e they search in, and produce as incumbents.

The entry mass is endogenously pinned down by the following free entry condition, which must hold when there is a positive entry mass M^e :

$$\int \max_{\Omega_j^e = \{w_j^e, \mathbf{d}_j', \mathbf{s}_j', \tilde{\mathbf{W}}_j'\}, \substack{d_j^e, l_j^e, x_j^e}} (1 - d_j^e) \left(P_{jt}(l_j^e)^\alpha - w_j^e l_j^e - c_f - \frac{c}{q(\theta(x_j^e))} l_j^e \right. \\ \left. + \beta(1 - \delta) \mathbb{E}_j \left[(1 - \mathbf{d}_j') \mathbf{J}(1, P_j, l_j^e, P_j', \Omega_j^e) \right] \right) dF_e(P_j) - c_e = 0, \quad (2.13)$$

where Ω_j^e is entrant firm j 's contract decision, which consists of the four components in (2.4). w_j^e , 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.²¹ Also, the distribution $F_e(P_j)$ of productivity is based on the entrant's initial prior about its own type ν_j , and $\mathbb{E}_j(\cdot)$ stands for the firm's updated posterior after observing P_j . Lastly, the firm is subject to the participation and incentive constraints (2.9) and (2.10) for retaining incumbent workers in the next period, and the following promise-keeping constraint for new hires in the current period:

$$\mathbf{W}(0, 0, 0, P_j, \Omega_j^e) \geq x_j^e \quad \text{for all workers } l_j^e. \quad (2.14)$$

²¹Note 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 Ω_j^e 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.

2.8 Labor Market Equilibrium

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

$$x^U = \operatorname{argmax}_x f(\theta(x))(x - \mathbf{U}), \quad (2.15)$$

where the outside option \mathbf{U} is given by (2.5). Incumbent workers at firm j solve

$$\mathbf{x}^E(a_j, \tilde{P}_{j,-1}, l_{j,-1}, P_j) = \operatorname{argmax}_x f(\theta(x))(x - \tilde{\mathbf{W}}(a_j, \tilde{P}_{j,-1}, l_{j,-1}, P_j)), \quad (2.16)$$

taking into account their outside option $\tilde{\mathbf{W}}_j$ provided by the current employer j . Equations (2.15) and (2.16) determine workers' optimal labor submarkets, where workers consider the trade-off between the value of a given contract and the corresponding probability of being matched.²²

On firms' side, (2.7), (2.11), (2.13), and (2.14) imply that all firms face the following same problem when choosing their optimal submarket x_j to search in:

$$x_j = \operatorname{argmin}_x \frac{c}{q(\theta(x))} + x, \quad (2.17)$$

independent of their state variables. This means that all firms are indifferent across the various submarkets x_j that are solutions to (2.17).

Labor market equilibrium is pinned down by the (possibly multiple) intersection points between the workers' and firms' choices (2.15), (2.16), and (2.17) with a CES matching function (with parameter γ). More details can be found in Online

²²Note that there exists ex-post heterogeneity among workers depending on their current employment status, although there is no ex-ante worker heterogeneity. This means that workers' choices and offers will be the same for all workers of a given employment status, being 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).

Appendix C.

2.9 Firm Distribution and Labor Market Clearing

Let $\mathbf{G}(a, \tilde{P}_{-1}, l_{-1})$ 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 all $a \geq 1, \tilde{P}_{-1}, l_{-1}$:

$$\begin{aligned} \mathbf{G}(a+1, \tilde{P}, l) & \quad (2.18) \\ & = (1 - \delta) \int_{l_{-1}} \int_{\tilde{P}_{-1}} \left(1 - \mathbf{d}(a, \tilde{P}_{-1}, l_{-1}, P)\right) \mathbb{I}_l \mathbf{G}(a, \tilde{P}_{-1}, l_{-1}) f_P(P) d\tilde{P}_{-1} dl_{-1}, \end{aligned}$$

subject to $P = e^{(a+1)\tilde{P} - a\tilde{P}_{-1}}$, where \mathbb{I}_l denotes an indicator function for firms choosing l (i.e., $\mathbf{I}(a, \tilde{P}_{-1}, l_{-1}, P) = l$). Note that $(\bar{\nu}, \sigma^2)$ are the mean and variance of the posterior distribution for a firm with age a and average log-productivity \tilde{P}_{-1} at the beginning of each period, and $f_P(\cdot)$ is the log-normal probability density function of productivity P , with the corresponding mean $\bar{\nu}$ and variance $\sigma^2 + \sigma_\varepsilon^2$.²³

We can track the stationary firm mass by iterating on the law of motion along with the following initial condition:

$$\mathbf{G}(1, \tilde{P}_{-1}, l_{-1}) = \begin{cases} M^e (1 - d^e(e^{\tilde{P}_{-1}})) f_e(e^{\tilde{P}_{-1}}) & \text{if } l^e(e^{\tilde{P}_{-1}}) = l_{-1}, d^e(e^{\tilde{P}_{-1}}) \neq 1 \\ 0 & \text{otherwise,} \end{cases}$$

where M^e is an entry mass, $f_e(\cdot)$ is the initial prior density of firm productivity, and d^e and l^e derived from (2.13).²⁴

²³(2.18) 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}_{-1} , productivity draw P , and size $\mathbf{I}(a, \tilde{P}_{-1}, l_{-1}, P) = l$.

²⁴The mass of firms with age 1, average productivity \tilde{P}_{-1} , and employment size l_{-1} consists of surviving entrants who realize initial productivity $P = e^{\tilde{P}_{-1}}$ and choose initial size $l^e(e^{\tilde{P}_{-1}}) = l_{-1}$.

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

$$\begin{aligned}
& \sum_{a \geq 1} \int_{\tilde{P}_{-1}} \int_{l_{-1}} \int_P \left\{ \left(\delta + (1 - \delta) (\mathbf{d}(a, \tilde{P}_{-1}, l_{-1}, P) \right. \right. \\
& \left. \left. + (1 - \mathbf{d}(a, \tilde{P}_{-1}, l_{-1}, P)) \mathbf{s}(a, \tilde{P}_{-1}, l_{-1}, P) \right) l_{-1} f_P(P) \mathbf{G}(a, \tilde{P}_{-1}, l_{-1}) \right\} dP dl_{-1} d\tilde{P}_{-1} \\
& = f(\theta(x^U)) \left(N - \sum_{a \geq 1} \int_{\tilde{P}_{-1}} \int_{l_{-1}} l_{-1} \mathbf{G}(a, \tilde{P}_{-1}, l_{-1}) dl_{-1} d\tilde{P}_{-1} \right), \tag{2.19}
\end{aligned}$$

which implies the inflow to the unemployment pool is equal to the outflow from the unemployment pool in the steady state equilibrium.²⁵

2.10 Stationary Recursive Competitive Equilibrium

Definition 1. A stationary recursive competitive equilibrium consists of: (i) the posteriors on types $\{\bar{v}, \sigma^2\}$; (ii) a set of value functions \mathbf{U} , $\mathbf{W}(a, \tilde{P}_{-1}, l_{-1}, P, \Omega)$, and $\mathbf{J}(a, \tilde{P}_{-1}, l_{-1}, P, \Omega)$ for workers and firms; (iii) a decision rule for unemployed workers x^U , for employed workers $\{\mathbf{x}^E\}$, for incumbent firms $\{\Omega = \{w, \mathbf{d}', \mathbf{s}', \tilde{\mathbf{W}}'\}, h, l, x\}$, and for entrants $\{\Omega^e = \{w^e, \mathbf{d}', \mathbf{s}', \tilde{\mathbf{W}}'\}, d^e, l^e, x^e\}$; (iv) the labor market tightness $\{\theta(x)\}$ for all active markets x ; (v) the stationary firm distribution $\mathbf{G}(a, \tilde{P}_{-1}, l_{-1})$; (vi) the mass of entrants M^e ; such that equations (2.2)-(2.3), (2.5)-(2.7), (2.13), (2.15)-(2.19) are satisfied, given the exogenous process for P , initial conditions (\bar{v}_0, σ_0^2) and $\mathbf{G}(1, \tilde{P}_{-1}, l_{-1})$, and $N = 1$.²⁶

²⁵The left-hand side of (2.19) 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.

²⁶The computation algorithm is described in Online Appendix F.

3 Model Implications

In this section, I discuss main model predictions for equilibrium wage.²⁷

Lemma 1. *Firm promise-keeping constraints (2.11) and (2.12) bind.*

Proof: From (2.6), (2.7), (2.11), and (2.12), each firm j optimally chooses the lowest possible $\{w_j(i)\}_i$ that complies with the promise-keeping constraints.

Proposition 1. *Equilibrium current wages are determined by workers' outside options and their expected future value (job prospects) at a given firm.*

Proof: See Online Appendix A.

Proposition 2. *Equilibrium current wages vary by firm age, controlling for workers' previous employment status, firm average and current productivity, and size.*

Proof: Following Proposition 1, the state contingency of contracts, the worker optimality condition (2.16), and the posteriors (2.2) and (2.3), given the worker's previous employment status, the wage is a function of firm state variables $(a, \tilde{P}_{-1}, l_{-1}, P)$. Thus, it depends on firm age even after controlling for the other firm state variables.²⁸

Next, workers' expected future value (job prospects) varies across firms as follows.

Lemma 2. *Workers expect future values at a firm in the following descending order: hiring or inactive (without quits) firms, quitting firms, firms laying off workers, and exiting firms. Proof: See Online 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

²⁷Other implications for uncertainty and welfare are derived in Online Appendix D and E.

²⁸The contract is contingent on firm state variables $(a, \tilde{P}_{-1}, l_{-1}, P)$, and the posterior beliefs are sufficiently characterized by firm age and average productivity (a, \tilde{P}_{-1}) . Through the optimality condition (2.16), workers' on-the-job search choice $x^{E'}$ is indeed a function of the promised utility \tilde{W}' in the contract.

by their employer and the workers' target utility in on-the-job search x^E . Taking into account (2.16), firms' choice of \tilde{W} depends on their desire to retain workers in the face of potential poaching by other firms.²⁹ Thus, expanding firms with more willingness to retain workers offer higher values to deter poaching than contracting firms.³⁰ Also, following (2.9), 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 options 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 strong continuation utility. Therefore, workers' future expected value is higher for firms with better posteriors and more (less) likelihood of keeping (losing) workers.

Proposition 3 demonstrates an analytic relationship between workers' future expected value and firm age (controlling for other firm characteristics) under a set of assumptions that enable analytic solutions.

Proposition 3. *Suppose the state-contingent utility \tilde{W} is an increasing function of P and has the same functional form across firm age. Then, given the firms' state variables $(\tilde{P}_{-1}, l_{-1}, P)$, there exists a cutoff for average productivity \tilde{P} above which workers' future expected value is lower for younger firms and another cutoff for average productivity \tilde{P} below which workers' future expected value is higher for*

²⁹In Online 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.

³⁰This is due to the vacancy cost as it is more costly to lose incumbents and hire new workers.

younger firms.³¹ *Proof: See Online Appendix A.*

When comparing two firms with the same observable characteristics but different ages, workers have lower (higher) expected future values at younger firms if their average productivity is above (below) a certain threshold, indicating them as a seemingly high (low)-performing firm.³² In other words, for high-performing firms with the same set of observable characteristics, workers' expected future value is lower at younger firms, while the opposite holds for low-performing firms. This stems from the limited information available about younger firms, leading workers to attribute good (bad) performance of young firms less to their good (bad) types.

This relates to the posterior mean in (2.2), which is a weighted sum of average performance and the initial prior mean with a higher weight put on average performance for older firms. With older firms having a longer track record, their posterior mean gets closer to the firms' observed performance. Consequently, if two firms exhibit equally good (bad) performance, the posterior beliefs about the younger firm are relatively worse (better) than for their mature counterpart.

Connecting this to Proposition 1, this insight applies to the wages as follows:

Proposition 4. *Suppose the assumptions in Proposition 3 hold. Then, given the firms' state variables $(\tilde{P}_{-1}, l_{-1}, P)$ and the average productivity \tilde{P} above a cutoff, equilibrium current wages (to a given type of new hires or to retain the same number of incumbent workers) are higher for younger firms than otherwise similar mature counterparts. Conversely, given the firms' state variables $(\tilde{P}_{-1}, l_{-1}, P)$ and the average productivity \tilde{P} below another cutoff, equilibrium current wages are lower for younger firms than otherwise similar mature counterparts, .*

³¹Note that the exact cutoffs can only be numerically solved, as will be presented in the following section. Numerical analysis reveals that both cutoffs are around the cross-sectional prior mean \bar{v}_0 on average, and this result holds over a broad parameter space.

³²Note that the equality holds when both firms are mature enough as the posterior converges to the firms' actual type.

Proof: This follows Propositions 1 and 3.

This result implies that high-performing younger firms need to pay higher current wages than otherwise similar mature firms to hire a given type of workers (either to hire an unemployed worker or to poach a worker employed at an outsider firm) or to retain the same amount of workers (i.e., conditional on the promised future utility x or \tilde{W}). On the other hand, low-performing younger firms can pay lower current wages than otherwise similar mature firms.³³ These age gaps are due to different job prospects across firms with different ages and history of performance.

4 Quantitative Analysis

I calibrate the model to quarterly data for the U.S. economy from 1998Q1 to 2014Q4. There are thirteen model parameters, where the first six are externally calibrated as in Table 1 and the remaining seven are internally calibrated as in Table 2.

External Calibration. I externally calibrate the parameters $\{\beta, \alpha, N, \bar{v}_0, \sigma_0, \sigma_\varepsilon\}$. I set the discount rate β to 0.99 to match a quarterly interest rate of 1.2%. I set the curvature of the revenue function α to be 0.65 as in Cooper et al. (2007). I normalize the total number of workers $N = 1$ and the initial prior mean $\bar{v}_0 = 0$. I estimate σ_0 and σ_ε using the LBD data. These are shown in Table 1.

Internal Calibration. I internally calibrate the remaining ones $\{b, \lambda, c, \gamma, c_e, c_f, \delta\}$ to jointly match the following target moments: (i) unemployment rate, (ii) employment-employment (EE) job transition rate, (iii) unemployment-employment (UE) rate, (iv) the elasticity of the UE rate with respect to the vacancy-employment ratio, (v) firm

³³Note that since firms are indifferent across the various labor submarkets along their indifference curve characterized by (2.17), there can be multiple active labor submarkets in equilibrium, and there is no systematic sorting between firm characteristics and the specific submarkets they choose. The wage relationships discussed above hold within each submarket, implying that on average, high-performing young firms pay wage premia, while low-performing young firms pay wage discounts.

Table 1: Externally Calibrated Parameters

Parameter	Definition	Value	From
β	Discount factor	0.99	Interest rate ($\beta = \frac{1}{(1+r)}$)
α	Revenue curvature	0.65	Cooper et. al. (2007)
N	Total number of workers	1	Normalization
ν_0	Initial prior on firm type mean	0	Normalization
σ_0	Initial prior on firm type dispersion	0.65	LBD
σ_ε	Idiosyncratic shock dispersion	0.47	LBD

entry rate, (vi) average firm size, and (vii) the share of young firms.³⁴

I apply the simulated method of moments (SMM) which minimizes the following objective function over the parameter space Θ :

$$\min_{\Theta} \sum_{i=1}^7 \left(\frac{M_i^{model}(\Theta) - M_i^{data}(\Theta)}{0.5(M_i^{model}(\Theta) + M_i^{data}(\Theta))} \right)^2,$$

which is the sum of squared percentage distances between the model-simulated moments $\{M_i^{model}(\Theta)\}_{i=1}^7$ and their counterpart moments in data $\{M_i^{data}(\Theta)\}_{i=1}^7$.

The following discusses the most relevant moment for each parameter. The unemployment insurance b is set to match the average BLS quarterly unemployment rate. The relative on-the-job search efficiency λ is used to match the EE rate as measured in the Census Job to Job flows database (J2J, a public version of the LEHD).³⁵ The vacancy cost c is used to target the UE rate in a quarter, which is calculated from BLS data as the average ratio of unemployment-to-employment flows relative to total unemployment. The CES matching function parameter γ is set to target the elasticity of unemployed workers' job-finding rate with respect to labor

³⁴The EE rate is defined as the share of employed workers who transition to a new job in the next period, the UE rate is defined as the share of unemployed workers who find a job in the next period, and the share of young firms is the share of firms aged five year or less in total firms.

³⁵To 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 "EEHire" in the J2J database. The J2J data begins in 2000Q2, and the average between 2000Q2 and 2014Q4 is used.

Table 2: Internally Calibrated Parameters

Parameter	Definition	Value	Targets	Data	Model
b	Unemployment insurance	0.50	Unemployment rate	0.061	0.069
λ	Relative on-the-job search efficiency	0.90	EE rate	0.033	0.032
c	Vacancy cost	0.54	UE rate	0.244	0.296
γ	CES matching function parameter	0.78	Elasticity of UE rate w.r.t. θ	0.720	0.674
c_e	Entry cost	18.57	Firm entry rate	0.089	0.089
c_f	Fixed operating cost	0.78	Average employment size	23.04	22.40
δ	Exogenous death shock	0.01	Share of young firms	0.365	0.332

Notes: Target moments are based on literature and the author's calculation with the BLS, BDS, and J2J data.

market tightness in [Shimer \(2005\)](#). The firm entry rate, average employment size, and the share of young firms are calculated from the Business Dynamics Statistics (BDS, a public version of the LBD) and are targeted to calibrate the entry cost c_e , the operating fixed cost c_f , and the exogenous death shock δ , respectively.³⁶

Cross-sectional Implications. With the calibrated model, I compare equilibrium wages across firm age, holding other firm state variables fixed. In particular, simulating the model, the nonlinear age effect on wages in [Proposition 4](#) is numerically determined around the prior mean \bar{v}_0 (i.e., the cutoffs are located around the prior mean \bar{v}_0 on average). In other words, given all else equal, high-performing young firms pay more than equally high-performing mature firms, while low-performing pay less than equally low-performing mature firms to a given type of workers.

[Figure 1](#) displays workers' expected future value (the top left panel) and the equilibrium current wage to hire unemployed workers (in the top right panel), to poach workers from a median firm (in the bottom left panel), and to retain incumbent workers (in the bottom right panel). The figure shows the wage differentials across firms of different ages, controlling for the workers' previous employment status and the firms' observable characteristics (equally-sized firms that have equal above-

³⁶The 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.

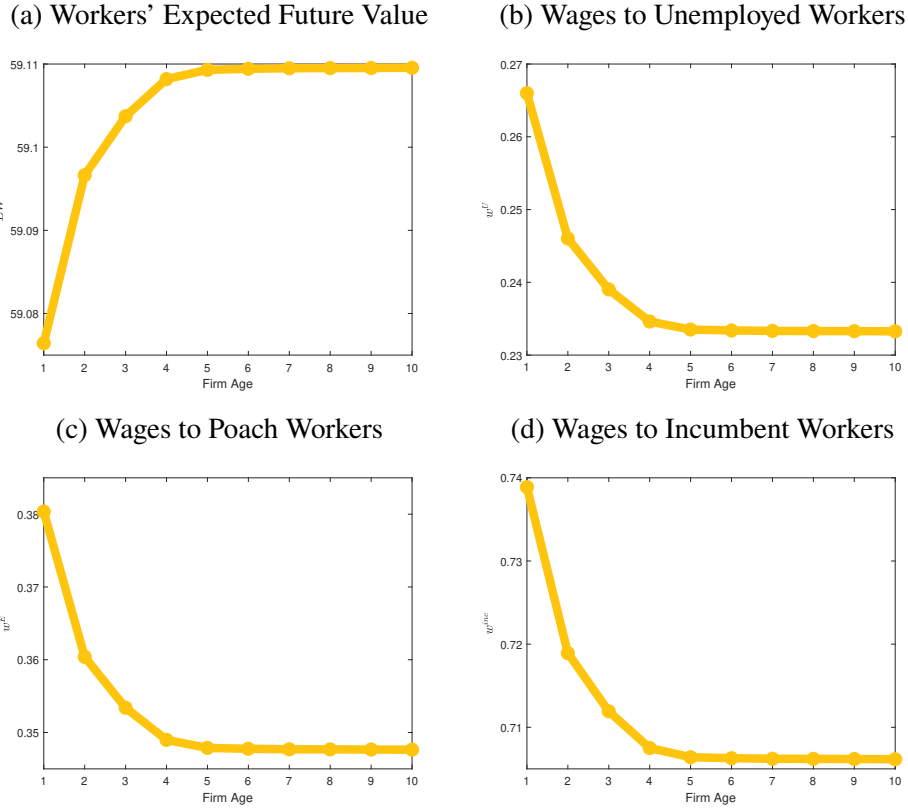


Figure 1: High-performing Firms (average size)

average productivity). This confirms that wages decline with firm age for high-performing firms. The counterparts for firms having low average productivity are displayed in Figure G.1 in the Appendix.

Aggregate Implications. I conduct a counterfactual analysis to draw out the aggregate implications of the job prospects mechanism, by changing the variance of productivity shocks σ_ε . From the baseline economy in which $\sigma_\varepsilon = 0.47$, I increase σ_ε to 0.58 (a one standard deviation increase) in the counterfactual economy.³⁷

Table 3 shows the results. First, having a higher σ_ε implies slower learning and higher noise surrounding young firms. Thus, the wages offered by high-performing

³⁷The standard deviation of σ_ε estimated in the LBD is approximately 0.11.

Table 3: Implications of Uncertainty

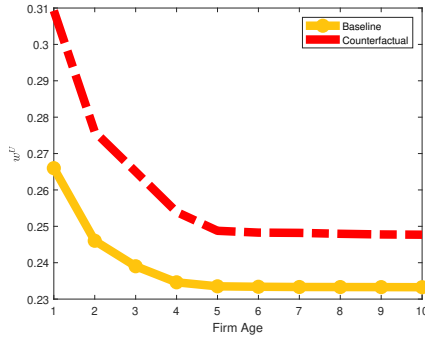
Description	Baseline ($\sigma_\epsilon = 0.47$)	High Uncertainty ($\sigma_\epsilon = 0.58$)	% Changes
Firm entry rate (%)	8.93	8.19	-8.29%
Share of young firms (%)	33.22	32.54	-2.05%
Olley-Pakes covariance	0.50	0.46	-7.84%
Aggregate productivity	1.07	0.95	-11.21%
Low performing firm share (%)	13.89	23.44	+68.75%
Average job filling rate (%)	72.10	70.89	-1.68%
Welfare	72.33	69.93	-3.32%

firms to both unemployed and employed workers increase, while those offered by low-performing firms decline. This implies the age effects on job prospects are amplified with higher uncertainty, which is consistent with the implications of uncertainty shown in Online Appendix D.

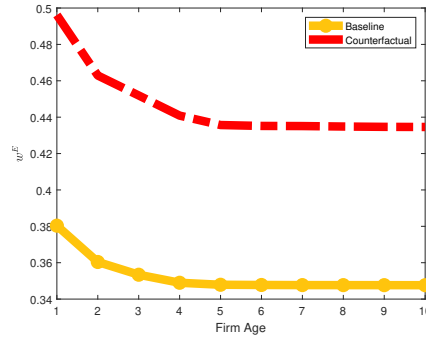
Furthermore, higher uncertainty about firm type also impacts macroeconomic variables. With higher uncertainty, firm entry rate and the young firm share of employment decrease. Furthermore, resources are reallocated toward low-performing firms and away from high-performing firms, as indicated by the lowered covariance between firm size and productivity as in [Olley and Pakes \(1996\)](#). Therefore, aggregate productivity is decreased.

The underlying intuition is simple. As the speed of learning about firm type slows down, the gap in job prospects between young and mature firms becomes larger. The current wage premia that high-performing young firms need at both the hiring and retention margins increase relative to otherwise similar established firms increases. Similarly, the wage discounts of low-performing young firms compared to their mature counterparts also persist longer in the counterfactual economy. [Figure 2](#) compares wage differentials for high-performing young firms between the baseline and counterfactual economies. The counterpart wages for low-performing firms are

(a) Wages to Unemployed Workers



(b) Wages to Poached Workers



(c) Wages to Incumbent Workers

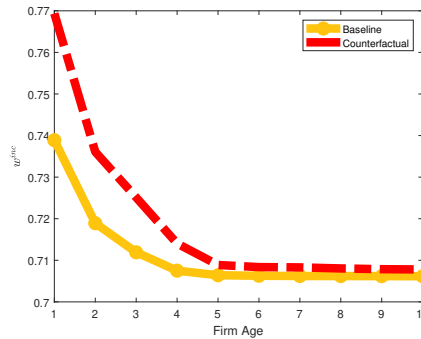


Figure 2: High-performing Firms: Baseline vs. Counterfactual (higher uncertainty)

shown in Figure G.2 in the Online Appendix. This makes mature low-performing firms no longer exit and continue operating in the counterfactual economy.

Thus, the growth of high-performing young firms is dampened, while low-performing young firms can survive longer and absorb more workers. This increases the mass of surviving firms with low productivity. Total unemployment goes down, because more firms survive, including potentially bad types, and this induces higher labor market tightness and hiring costs. Consequently, the firm entry rate declines and the activity of young firms with high growth potential is muted. These results suggest that magnified uncertainty about job prospects can be a source of decreased young firm activities and lowered allocative efficiency in the economy.

5 Empirical Analysis

Data and Measures. To test the model predictions, I construct a comprehensive dataset containing firm-level measures, worker characteristics, employment records, and earnings, using the Longitudinal Business Database (LBD) and Longitudinal Employer Household Dynamics (LEHD) from 1998 to 2014, both of which are hosted by the U.S. Census Bureau.

The LBD tracks the universe of U.S. business establishments and firms with at least one paid employee, annually from 1976 onward. The LEHD is constructed from quarterly Unemployment Insurance (UI) system wage reports of states participating in the program, which collect quarterly earnings, employment, and demographic information. I have access to 29 states covering over 60 percent of U.S. private sector employment. I link the LEHD to the LBD and identify worker heterogeneity, employment history, and employers associated with each job held by workers.

Regarding firm variables, 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).³⁸ In the 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.³⁹ Further details about the data construction can be found in Online Appendix [H](#).

Firm Type Learning Process. Using firm-level revenue productivity, I estimate

³⁸The revenue per worker is highly correlated with TFPQ within industries.

³⁹For 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.

a firm type learning process in my data. First, I take the deviation of firm-level log revenue productivity from its industry-year mean, and project the demeaned log productivity on its own lag. Thus, I estimate the following regression:

$$\ln P_{jt} = \rho \ln P_{jt-1} + \nu_j + \varepsilon_{jt}, \quad (5.20)$$

where $\ln P_{jt}$ refers to the log real revenue productivity for firm j demeaned at the industry-year level, and ν_j is a firm-level fixed effect. I include the lag term $\ln P_{jt-1}$ to factor out the productivity persistence observed in the data.⁴⁰ Removing industry-year means controls for the effects of fundamental industry-specific differences in technology or production processes as well as time trends or cyclical shocks.

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} . This is the term that I map into the model productivity estimates, which I denote henceforth as $\ln \hat{P}_{jt}$, i.e., $\ln \hat{P}_{jt} \equiv \hat{\nu}_j + \hat{\varepsilon}_{jt}$. Then, I define noise in the learning process as the variance of the estimated residual $\hat{\varepsilon}_{jt}$ from (5.20).

Next, I construct average productivity (\tilde{P}_{jt-1}) over the firm life-cycle for each firm using the productivity estimates (\hat{P}_{jt}) and longitudinal firm identifiers. Here, I limit the sample to firms that have consecutively non-missing observations of $\ln \hat{P}_{jt}$ from their birth to properly track the accumulation of firm performance and the learning

⁴⁰To 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 \(1998\)](#).

process in each period.⁴¹ I define it as follows:

$$\tilde{P}_{jt-1} \equiv \frac{\sum_{\tau=t-a_{jt}}^{t-1} \ln \hat{P}_{j\tau}}{a_{jt}}, \quad (5.21)$$

where a_{jt} is the age of firm j in year t . I use $\ln \hat{P}_{jt}$ and \tilde{P}_{jt-1} in my regression below as measures representing the current and average productivity levels, respectively.

I indicate high-performing firms as those having average productivity above the within-industry cross-sectional mean of firm-level estimated prior mean productivity:

$$\mathbb{I}_{jt}^H \equiv \begin{cases} 1 & \text{if } \tilde{P}_{jt-1} > \frac{\sum_{j \in g(j,t)} \hat{\nu}_j}{N_{g(j,t)}} \\ 0 & \text{otherwise} \end{cases}, \quad (5.22)$$

where $N_{g(j,t)}$ is the number of firms in industry $g(j, t)$ in a given year t .⁴²

Uncertainty Measure. Using the estimated parameters from (5.20), I estimate the within-industry cross-sectional dispersion of $\hat{\varepsilon}_{jt}$ and the fixed effect estimates $\hat{\nu}_j$, respectively, on a yearly basis. I denote these estimates by $\hat{\sigma}_{\varepsilon gt}$ and $\hat{\sigma}_{0gt}$, respectively, for each industry g . I use the ratio of the former to the latter to measure industry-level uncertainty as follows, which is known as the “noise-to-signal” ratio:

$$Uncertainty_{gt} \equiv \frac{\hat{\sigma}_{\varepsilon gt}}{\hat{\sigma}_{0gt}}. \quad (5.23)$$

Note that the denominator can be translated into the initial dispersion of firm fundamentals, representing the informativeness of signals in each industry. This indicates

⁴¹This forms the main regression sample with summary statistics available in Online Appendix H.3.

⁴²This 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 degree of uncertainty conditional on this fundamental dispersion, to take into account inherent variations in the informativeness of signals across industries.

5.1 Baseline Two-stage Earnings Regression

To test the main job prospects channel, I use the following two-stage earnings regression at the individual level. In the first stage, I use workers' full-quarter earnings and take out the effect of worker heterogeneity. I get earnings residuals subtracting worker and year fixed effects and the effects of worker time-varying characteristics. In the second stage, I regress the earnings residuals on the young firm indicator, the high-performing firm indicator and their interaction, controlling for the worker's previous employment status, the current firm's time-varying characteristics, as well as the fixed effects of industry and state, respectively.⁴³ This enables me to estimate how wages vary by firm ages and depend on workers' job prospects at the firm (tracked by firm age and average productivity), all else equal.

Stage 1: Estimating Earnings Residuals. In the first stage, I estimate earnings residuals controlling for worker age, and worker and year fixed effects, as follows:

$$y_{it} = \delta_i + \eta_t + X_{it}\gamma + \epsilon_{it}, \quad (5.24)$$

where y_{it} is the logarithm of the Q1 earnings of individual i in year t , δ_i is a time-invariant individual 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.^{44,45}

⁴³As a baseline, I control for the worker's previous employment status, using the AKM firm fixed effect estimate for the previous employer and a dummy indicating if the worker was not employed in the previous period. The AKM firm fixed effect is the firm fixed effect obtained from estimating the standard two-way fixed-effect framework in my data, following [Abowd et al. \(1999\)](#).

⁴⁴This follows [Card et al. \(2016\)](#), [Crane et al. \(2018\)](#), and [Haltiwanger et al. \(2021\)](#). As a robustness check, I additionally control for the effect of worker skills (the highest education attainment).

⁴⁵In 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

Stage 2: Wage Differentials across Firm Age and Performance. In the second stage, I use the estimated earnings residuals $\hat{\epsilon}_{it}$ from (5.24) and regress it on the young firm dummy, the high-performing firm dummy in (5.22), and their interaction.

Equation (5.25) presents the second stage regression, where the main coefficients of interest are β_1 and β_2 , which capture the earnings differentials associated with young firms depending on their average performance.

$$\begin{aligned} \hat{\epsilon}_{it} = & \beta_1 Young_{j(i,t)t} + \beta_2 Young_{j(i,t)t} \times \mathbb{I}_{j(i,t)t}^H + \beta_3 \mathbb{I}_{j(i,t)t}^H + Z_{j(i,t)t} \gamma_1 \\ & + Z_{j(i,t-1)} \gamma_2 + \mu_{g(j(i,t))} + \mu_{s(j(i,t))} + \alpha + \xi_{it} \end{aligned} \quad (5.25)$$

The regression is at the worker-year level, where $\hat{\epsilon}_{it}$ is the earnings residual of worker i in a given year t , $j(i, t)$ is the employer where worker i is employed at t , $Young_{j(i,t)t}$ is the young firm indicator for firm $j(i, t)$, $\mathbb{I}_{j(i,t)t}^H$ is the high performing firm indicator for firm $j(i, t)$, $Z_{j(i,t)t}$ is a vector of controls for time-varying properties of firm $j(i, t)$, and $Z_{j(i,t-1)}$ is a vector of controls for the worker's employer in the previous period. To be consistent with the model, I include average productivity, current productivity, and employment size of firm $j(i, t)$ in $Z_{j(i,t)t}$. For $Z_{j(i,t-1)}$, as a baseline, I use the AKM firm fixed effect associated with the worker's previous employer along with the non-employment indicator.⁴⁶ Lastly, the regression includes the fixed effects of industry and state that the firm belongs to in year t , $\mu_{g(j(i,t))}$ and $\mu_{s(j(i,t))}$, respectively.

explicitly using dummy variables to account for the fixed effects.

⁴⁶Following the discussion above, I control for workers' previous employment status by controlling for the fixed effect for the firm where each worker was employed in the previous period. 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 following [Abowd et al. \(1999\)](#). Note that 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. Also, as an additional robustness test, I use earnings paid by the previous employer. For workers who are not employed in any states in the previous period, I assign a non-employment dummy variable to them. More details are available in [Online Appendix H](#).

Table 4: Wage Differentials for Young Firms

	(1)	(2)
	Earnings Residuals	Earnings Residuals
Young firm	-0.002*** (0.001)	-0.003*** (0.001)
Young firm \times High performing firm	0.015*** (0.001)	0.016*** (0.001)
High performing firm	0.002 (0.001)	0.002 (0.001)
Observations	50,170,000	50,170,000
Fixed effects	Industry, State	Industry, State
Controls	Full (current size)	Full (lagged size)

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

Note that the firm variables have the same values across all workers employed at that firm at t (i.e., workers employed at the SEINs associated with the same firm identifier). The novelty in (5.25) comes from the coefficients 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 history of performance.

Table 4 presents the regression results with the full set of controls to be consistent with the model.⁴⁷ The first column controls for the current value of firm size and the second column uses the lagged value of it.

In the regression, the impact of being a young firm on earnings depends on β_1 and $\beta_2 \mathbb{I}_{j(i,t)}^H$, and the total impact depends on whether the observed average productivity $\tilde{P}_{j(i,t)}$ is below or above the industry mean. For low-performing firms, the wage

⁴⁷For the sake of space, I only present the main coefficients. The full results can be found in Table I2 in Appendix.

differential for young firms is given by β_1 . For high-performing firms, the wage differential for young firms is given by $\beta_1 + \beta_2$. Table 4 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.⁴⁸ The results indicate that high-performing young firms pay more than their otherwise similar mature counterparts, while low performing young firms pay less. This is consistent with the model prediction about young firms' wage differentials through the channel of worker learning and job prospects about firms.

5.2 Robustness Checks

To validate the baseline results, several robustness checks are performed and reported in Online Appendix J.

Firm Size Effects. Firm size is highly correlated with firm age, and the firm size distribution varies by different firm age.⁴⁹ This correlation may lead the size covariate to absorb firm age effects in the baseline regression. To check this, I run regressions without controlling for firm size (with various combinations of firm controls), and the results stay robust as in Online Appendix Table J5.

Correcting Sample Selection Bias. Another potential source of bias is sample selection. The current sample is drawn from the population of U.S. firms with consecutively non-missing observations of revenue data, and workers matched with these firms. Therefore, the sample drops firms with missing revenue data throughout their lifecycle, primarily affecting older firms. To mitigate potential selection bias, I estimate a propensity score model and weight the regression sample with inverse propensity score weights.⁵⁰ The results remain consistent, as shown in Online

⁴⁸The statistical significance of $\hat{\beta}_1 + \hat{\beta}_2$ has been confirmed by the delta method.

⁴⁹For instance, most young firms tend to be small in the U.S. economy.

⁵⁰Following Haltiwanger et al. (2017), I use logistic regressions with a dependent variable equal to one if the firm belongs to the current sample and zero otherwise, along with firm characteristics such as firm size, age, employment growth rate, industry, and a multi-unit status indicator from the

Appendix Table J6.

Standard Error Bootstrapping. The high-performing firm indicator as well as firm control variables in the second-stage regression are constructed based on estimates from the regression in (5.20). This might cause the reported standard errors in Table 4 to be incorrect. To address this, I estimate the standard errors with bootstrapping and check the robustness of the results.⁵¹ The statistical significance of the coefficient estimates stays robust, as presented in Online Appendix Table J7.

Unobserved Worker Characteristics. In the current specification, I control for the effect of worker age and their previous employment status, along with worker fixed effects. However, alternative interpretations of the main results may arise from other potential sources related to unobserved time-varying worker characteristics. For instance, high-performing young firms may demand workers with more experience or longer tenure than their mature counterparts given the burden of training costs, which may result in the earnings premia paid by high-performing young firms.

To rule out such cases, I control for earnings on the previous job as a proxy of worker tenure or experience. The previous earnings can also measure the workers' place on the job ladder in alignment with the model.⁵² The results are robust even after controlling for earnings on the previous job, as in Online Appendix Table J8.

Moreover, worker skills can influence the level of earnings paid by employers. If

universe of the LBD. Using inverse probability weights calculated from the predicted values from the logistic regression, I weight the sample and rerun the regressions.

⁵¹To 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 coefficient.

⁵²Based on the model, using the AKM fixed effect might be conservative, as the equilibrium wages at both the hiring and retention margins (eventually) only depend on whether workers came from the unemployment pool, from an employer that wanted to expand or stay inactive, or from an employer that cut back on their size. Thus, another potential proxy to control for the worker's previous job and their place on the job ladder in the previous period would be the earnings associated with the previous employer (still also controlling for the non-employment status indicator).

there are sorting patterns between worker skills and firm ages, the current results might reflect the impact of unobserved worker heterogeneity rather than the effect of uncertainty surrounding young firms. To address this concern, I use the highest education level attained by workers as a proxy for worker skills and include it as an additional control variable in the first-stage regression. Online Appendix Table J9 displays the results of the second-stage regression using earnings residuals that remove the effect of worker skills. This confirms the robustness of the findings.

Another unobservable worker characteristic that could influence results is their preference for risks. Despite the current specification controlling for firms' time-varying characteristics, there could still be higher risks associated with young firms in general, which may not be fully taken out. Therefore, if the risk preference of workers is not properly taken out, given that it is hard to measure in the data, the current result may reflect the effect of their risk preference.⁵³ To test this, I further control for the variance of young firm productivity shocks as a proxy for the riskiness of young firms. The results are robust as shown in Online Appendix Table J10.

Firm-level Analysis. I estimate the baseline firm fixed effect (to control for the effect of worker outside options) at the SEIN level. Alternatively, I use the fixed effects estimated at the firm level with longitudinal firm identifiers. The result is not affected as displayed in Online Appendix Table J11. Additionally, I conduct the second-stage regression at the firm level, utilizing the within-firm average of the earnings residuals as the main dependent variable and controlling for the same set of firm characteristics. Online Appendix Table J12 confirms the robustness of the results. This indicates that even after taking the average of the earnings differentials across various types of workers from different origins, the same results hold.⁵⁴

⁵³For instance, the current earnings differentials for young firms (for both high-performing and low-performing firms) may be influenced by the presence of risk preference of workers if risk-averse (or risk-loving) workers are selectively sorted into these firms and compensated more (or less).

⁵⁴This is another aspect align with the model, where firms randomly choose from different types

Table 5: The Effect of Wage Differentials on Firm Outcomes

A. Raw Productivity	(1)	(2)	(3)	(4)
	Hire (firm level)	Hire (SEIN level)	Employment Growth (log diff)	Employment Growth (DHS)
Average Earnings Residuals	-0.520*** (0.020)	-0.387*** (0.024)	-0.015*** (0.000)	-0.018*** (0.000)
Observations	6,959,000	6,959,000	6,959,000	6,959,000
Fixed effects	Industry, State	Industry, State	Industry, State	Industry, State
Controls	P, size, age	P, size, age	P, size, age	P, size, age

B. Estimated Productivity	(1)	(2)	(3)	(4)
	Hire (firm level)	Hire (SEIN level)	Employment Growth (log diff)	Employment Growth (DHS)
Average Earnings Residuals	-0.498*** (0.0195)	-0.369*** (0.0244)	-0.012*** (0.0003)	-0.015*** (0.0003)
Observations	6,959,000	6,959,000	6,959,000	6,959,000
Fixed effects	Industry, State	Industry, State	Industry, State	Industry, State
Controls	avg.P, P, size, age	avg.P, P, size, age	avg.P, P, size, age	avg.P, P, size, age

Notes: The table reports the effect of earnings residuals on firm-level outcomes. Firm controls include firm productivity, log employment size, and age. Note that Panel A uses the raw value of firm productivity, while Panel B adopts the cross-time average value as well as the current value of the estimated firm productivity as in the main regressions. Column (1) uses the firm-level total new hires, and column (2) uses the average of the SEIN-level new hires. Observation counts are rounded to the nearest 10,000 to avoid potential disclosure risks. Estimates for constant, and industry, state fixed effects are suppressed. Observations are unweighted. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5.3 The Impact of Wage Differentials on Firm Outcomes

The following regression is used to see how the earnings differentials impact firm outcomes:

$$Y_{jt} = \beta \hat{\epsilon}_{jt} + Z_{jt}\gamma + \mu_{g(j,t)} + \mu_{s(j,t)} + \alpha + \xi_{jt}, \quad (5.26)$$

where Y_{jt} is either the number of new hires or employment growth of firm j , $\hat{\epsilon}_{jt}$ denotes the within-firm average earnings residuals, averaging $\hat{\epsilon}_{it}$ across workers i hired at firm $j(i, t)$, Z_{jt} denotes the set of firm controls, including size, productivity, and age. Industry and state fixed effects, $\mu_{g(j,t)}$ and $\mu_{s(j,t)}$, are taken out.

Table 5 shows the results indicating negative impacts of earnings residuals on of workers along their indifference curve. The firm-level earnings differentials move in the same direction as the worker-level earnings, controlling for worker ex-post heterogeneity.

firm hiring and employment growth.⁵⁵ It is important to note that the results isolate the effects from firm size, productivity, and age. This supports the identification of earnings differentials attributed to uncertain prospects about firms, ruling out alternative hypotheses related to performance pay or surplus sharing.⁵⁶ The results are robust to applying inverse propensity score weights to avoid potential sampling bias, as shown in Online Appendix Table J13.

5.4 The Impact of Uncertainty on Wages and Aggregate Outcomes

Cross-sectional Implications on Wage Differentials. In the model, higher uncertainty drags out the speed of learning and pronounces the wage differentials for young firms. To test this implication, I add additional interaction terms involving the industry-level uncertainty measure (5.23) to the baseline regression, as follows:

$$\begin{aligned}
\hat{\epsilon}_{it} = & \beta_1 Young_{j(i,t)t} + \beta_2 Young_{j(i,t)t} \times \mathbb{I}_{j(i,t)t}^H + \beta_3 Young_{j(i,t)t} \times Uncertainty_{gt} \\
& + \beta_4 Young_{j(i,t)t} \times \mathbb{I}_{j(i,t)t}^H \times Uncertainty_{g(j,t)t} + \beta_5 Uncertainty_{gt} \\
& + \beta_6 \mathbb{I}_{j(i,t)t}^H \times Uncertainty_{gt} + \beta_7 \mathbb{I}_{j(i,t)t}^H + Z_{j(i,t)t} \gamma_1 + Z_{j(i,t-1)t} \gamma_2 \\
& + \mu_{g(j(i,t))} + \mu_{s(j(i,t))} + \alpha + \xi_{it},
\end{aligned} \tag{5.27}$$

where $Uncertainty_{g(j,t)t}$ is the value of the uncertainty measure in (5.23) for the main industry that firm $j(i,t)$ is associated with in year t . Here, I use both current and lagged values of uncertainty to mitigate potential issues of reverse causality. I include sector fixed effects $\mu_{g(j(i,t))}$ at the NAICS2 level. This allows for variations in uncertainty across industries while controlling for fundamental differences across

⁵⁵New hires are defined by either the total number of newly hired workers at the firm level or the average of the number of newly hired workers at the SEIN level. For firm productivity, Panel A uses the raw value P_{jt} , and Panel B alternatively uses the estimated cumulative average and current productivity (based on \hat{P}_{jt}) as in the baseline regression.

⁵⁶To conserve space as before, the full results are available in Online Appendix Table I3.

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

	(1)	(2)	(3)	(4)
	Earnings Residuals	Earnings Residuals	Earnings Residuals	Earnings Residuals
Young firm	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.002)	-0.002 (0.002)
Young firm × High performing firm	0.012*** (0.002)	0.012*** (0.002)	0.003 (0.002)	0.005** (0.002)
Young firm × Uncertainty (at t)	-0.004** (0.002)	-0.004*** (0.002)		
Young firm × High performing firm × Uncertainty (at t)	0.006*** (0.002)	0.006*** (0.002)		
Young firm × Uncertainty (at $t - 1$)			-0.005** (0.002)	-0.004* (0.002)
Young firm × High performing firm × Uncertainty (at $t - 1$)			0.016*** (0.003)	0.015*** (0.003)
Observations	50,170,000	50,170,000	50,170,000	50,170,000
Fixed effects	State, Sector	State, Sector	State, Sector	State, Sector
Controls	Full (current size)	Full (lagged size)	Full (current size)	Full (lagged size)

Notes: The table reports the earnings regression interacted with industry-level uncertainty. The set of controls for firm characteristics and worker previous employment status remain the same as in the baseline regression. Columns (1) and (3) incorporate the current value of firm size, while columns (2) and (4) use the lagged value of firm size. In addition, columns (1) and (2) are based on the current level of uncertainty, whereas columns (3) and (4) utilize the lagged uncertainty 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

sectors. The regression captures how the wage differentials associated with young firms vary across different industries with different levels of uncertainty.

Table 6 displays the results with columns (1) and (2) based on the current value of uncertainty and (3) and (4) based on the lagged value.⁵⁷ As before, columns (1) and (3) control for the current value of firm size, and columns (2) and (4) use the lagged value. The table shows that the coefficient estimate of the triple interaction term between the young firm indicator, the high-performing firm indicator and the uncertainty measure is positive, such that $\hat{\beta}_3 + \hat{\beta}_4 > 0$, which is consistent with the model prediction that higher uncertainty increases the wage premium that high-performing young firms need to pay.⁵⁸ Furthermore, the coefficient estimate for the interaction between the young firm indicator and the uncertainty measure is negative, i.e., $\beta_3 < 0$, which is also in line with the model result that the wage

⁵⁷Refer to Online Appendix Table I4 for the full table.

⁵⁸Again, the delta method has been applied to confirm its statistical significance.

Table 7: Aggregate Implications of Uncertainty

	(1)	(2)	(3)	(4)	(5)
	Entry rate	Young firm share	HG young firm share	HG young firm growth	Productivity
Uncertainty	-0.009*** (0.002)	-0.013*** (0.005)	-0.010*** (0.003)	-0.020*** (0.005)	-0.227*** (0.011)
Observations	4,300	4,300	4,300	4,300	4,300
Fixed effects	Industry, Year	Industry, Year	Industry, Year	Industry, Year	Industry, Year

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

discounts for low-performing young firms gets larger as uncertainty rises. This holds for all columns.

Macroeconomic Implications. Next, I test the aggregate implications of the model. The calibrated model predicts increased uncertainty to reduce firm entry, young firm activity, and aggregate productivity by slowing down learning and selection. First, I estimate the following industry-level panel regression:

$$Y_{gt} = \beta \text{Uncertainty}_{gt} + \delta_g + \delta_t + \epsilon_{gt}, \quad (5.28)$$

where Y_{gt} is either the firm entry rate, the share of young firms, the share of high-growth young firms, the average employment growth rate of high-growth young firms, or the average productivity at the industry level (industry g) in a given year t .⁵⁹ Industry and year fixed effects, δ_g and δ_t , are taken out, respectively.

Table 7 displays the results, showing that firm entry, young firm growth, and aggregate productivity are negatively associated with uncertainty at the industry level. This is a cross-sectional association between uncertainty and aggregate firm

⁵⁹High-growth young firms are those above the 90th percentile of the industry employment growth distribution and aged five years or less.

Table 8: Aggregate Implications of Uncertainty (long run)

A. Industry FE	(1)	(2)	(3)	(4)	(5)
	Entry rate	Young firm share	HG young firm share	HG young firm growth	Productivity
Uncertainty	-0.126*** (0.020)	-0.372*** (0.071)	-0.183*** (0.026)	-0.279*** (0.046)	-2.06*** (0.288)
Observations	250	250	250	250	250

B. Long-run Avg.	(1)	(2)	(3)	(4)	(5)
	Entry rate	Young firm share	HG young firm share	HG young firm growth	Productivity
Uncertainty	-0.126*** (0.020)	-0.372*** (0.071)	-0.183*** (0.026)	-0.279*** (0.046)	-2.09*** (0.289)
Observations	250	250	250	250	250

Notes: The table reports results for regression of the long-run value of firm entry, the share and growth of young firms, and aggregate productivity in each column on the counterpart for uncertainty at the industry level. Panel A is based on the industry fixed effects, and Panel B uses the long-run average value of each measure. Observation counts are rounded to the nearest 50 to avoid potential disclosure risks. Estimates for constant are suppressed. Observations are unweighted. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

dynamics at a high frequency level.

I further examine their long-run relationship as in the steady-state economy of the model by constructing two measures to proxy the steady-state level of the variables for each industry: i) industry fixed effects and ii) the long-run average of the variables across the entire sample years. I then run the following cross-sectional regression:

$$\hat{\delta}_g^Y = \beta \hat{\delta}_g^{Uncertainty} + \alpha + \epsilon_g, \quad (5.29)$$

where $\hat{\delta}_g^Y$ and $\hat{\delta}_g^{Uncertainty}$ represent the long-run measures for Y and uncertainty.⁶⁰

The results are displayed in Table 8, with Panel A presenting the estimates based on industry fixed effects and Panel B based on the long-run average measures.

⁶⁰The 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.

These findings suggest a negative and statistically significant correlation between uncertainty and the aggregate variables exists even in the long run.

These findings, in conjunction with the previous results, indicate dampened young firm activities and aggregate productivity in industries with higher uncertainty, where the wage differentials for young firms are more pronounced. This aligns with the aggregate implications in the model.

6 Conclusion

In this paper, I study how workers' job prospects impact the wage and growth of young firms, as well as aggregate outcomes in the economy. The paper develops a rich theoretical framework linking firm dynamics to labor market frictions and leverages micro-level administrative data to test the model's predictions. The following set of implications are found in the model and supported in the data: i) the uncertain job prospects of workers result in wage premia for high-performing young firms and wage discounts for low-performing young firms, relative to their observationally identical mature counterparts; ii) increasing uncertainty about young firms amplifies both types of wage differentials for young firms; and iii) heightened uncertainty dampens the growth of high potential young firms, redirects labor inputs to low-performing young firms, and diminishes overall business dynamism and productivity in the economy. In summary, this paper provides a foundation for understanding young firm dynamics and aggregate implications through a novel channel of worker job prospects.

Supplementary Materials. Additional supplementary materials can be accessed in the [Online Appendix](#) of this article.

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