Safety in Unemployment and Risky Experimentation of Young Firms*

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Abstract

We develop a theory in which a lower cost of unemployment increases workers' willingness to join risky young firms, lowering negotiated wages relative to safer firms. These lower wages encourage young firms to undertake high-upside experimentation, raising aggregate productivity. Using Danish matched employer–employee data and regional labor-market variation, we show that higher job-finding rates are associated with lower wage differentials between experimenting and non-experimenting young firms, both across firms and within firms hiring across multiple areas. A randomized survey experiment supports the worker-side mechanism: worsening unemployment prospects increases the wage premium workers require to accept employment at higher-failure-risk young firms.

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1 Introduction

High-growth young firms account for a disproportionate share of productivity growth (Haltiwanger et al., 2016). Yet such firms are rare because exceptional growth typically requires experimentation from birth—that is, pursuing a novel business idea with highly uncertain market potential ex ante, rather than replicating an existing activity with relatively predictable outcomes (Hurst and Pugsley, 2011; Sterk et al., 2021; Akcigit and Kerr, 2018). These experimental strategies are inherently risky and often fail (Kerr et al., 2014). A central but underappreciated feature of this risk is that it is borne jointly: when experimentation fails, workers—not just entrepreneurs—face job-loss risk. This paper shows that the cost of unemployment shapes how that risk is reflected in wages—a cost determined by expected unemployment duration, unemployment insurance generosity, and the earnings and human-capital losses that may persist after reemployment. When the cost of unemployment is lower, workers require a smaller wage differential to join riskier young firms, lowering their relative labor costs and making experimentation more attractive. We document this unemployment channel in Danish data and quantify its implications for experimentation and aggregate productivity.

We formalize this mechanism in a model with heterogeneous, multi-worker firms, endogenous experimentation, and a frictional labor market with alternating-offer wage bargaining (AOB) à la Hall and Milgrom (2008). AOB links negotiated wages to the value of unemployment through both the worker's outside option and the cost of delay. This structure implies that changes in unemployment conditions shift wage differentials across firms with different separation risk: when unemployment becomes less costly, workers at riskier firms—who face a higher separation risk—benefit disproportionately, and the wage differential required to work at risky young firms falls relative to safe firms. Notably, under AOB, this mechanism arises also under risk neutrality. We adopt AOB rather than standard Nash bargaining because, under Nash, wages respond to unemployment conditions uniformly across firms, independently of separation risk—a restriction that is at odds with our empirical evidence.

We use the job-finding rate as the key shifter of the value of unemployment in the model-based quantitative analysis, because variation in job-finding rates provides a useful source of variation for our empirical tests. In the quantitative analysis, we trace how changes in job-finding conditions propagate into entry, experimentation, and productivity. Since the job-finding rate is an endogenous equilibrium object, it can only be shifted by exogenous parameter changes. Accordingly, our main counterfactual varies the scale parameter governing firms' vacancy-posting (job-creation) costs, and we study the resulting propagation mechanism: a change in vacancy costs moves equilibrium job finding, which shifts the value of unemployment and thereby alters wage differentials between experimenting and non-experimenting firms.

Rather than modeling specific institutions one by one, we interpret this counterfactual as a reduced-form way of capturing policy and institutional forces that affect job creation, closely following Engbom (2022). Institutions such as labor taxes, employment protection legislation, and business regulations are all known to raise hiring costs (Hopenhayn and Rogerson, 1993; Pries and Rogerson, 2005), providing a rationale for modeling them through a unified cost of job creation.[1] While in reality these institutions operate through distinct channels and may have heterogeneous effects on the economy, we abstract from this complexity. Our objective is not to estimate institution-specific effects but to isolate a common propagation mechanism: how shifts in job finding—and hence the value of unemployment—alter wage differentials between experimenting and non-experimenting firms.

First, we explore the overall effects of a decrease in job creation costs that raise the job-finding rate of unemployed workers by 10 percentage points. The direct impact of this policy is an increase in firm profits and entry. Greater firm entry reduces average firm size, which boosts productivity due to decreasing returns to scale. At the same time—and most relevant for our purposes—the rise in labor demand increases the value of being unemployed, as it shortens unemployment duration. This change affects the wage bargaining process, leading to lower wages at risky young firms and higher wages at safer firms. The resulting shift in relative wages encourages a greater share of entrants to pursue risky experimentation, further contributing to aggregate productivity. Overall, productivity increases by approximately 1%.

To isolate the importance of this propagation mechanism, we conduct a counterfactual analysis in which the value of unemployment is held fixed at its baseline level while job creation costs decrease. In this scenario, there is virtually no differential wage response between risky and safe young firms, so the share of entrants undertaking risky experimentation remains nearly unchanged—highlighting the central role of

[1] Summarizing various policies into a single reduced-form object resembles, in spirit, the *indirect* approach used by Restuccia and Rogerson (2017) and Hsieh and Klenow (2009).

the unemployment channel in amplifying productivity gains. While productivity still rises due to increased entry from lower job-creation costs, the gains are only about half as large, confirming that the unemployment channel accounts for a substantial portion of the overall productivity effect.

Motivated by this counterfactual evidence, we take the mechanism to the data and implement a *direct* microeconometric test of the unemployment channel. The theory predicts that an increase in the job-finding rate decreases wages at risky, experimenting young firms relative to safe young firms, reducing the risky–safe wage differential. In the empirical analysis, we exploit geographic variation in Denmark by measuring job-finding rates at the commuting-zone level and relating them to wage differentials across firm types. We do so using Danish matched employer–employee data covering 2008–2023, comprising roughly 16 million worker–year observations. We operationalize this prediction by constructing a model-consistent firm-level measure of experimentation from the permanent component of sales growth, estimated within industry–entry cohorts. Intuitively, the model maps experimentation to greater dispersion in ex-post permanent productivity; empirically, we recover each firm's permanent growth type and classify "experimenting" firms as tail types of that distribution, treating the remainder as safe.

As a validity check on the constructed experimentation measure, we document two non-targeted diagnostics that align with model implications. First, firms classified as experimenting exhibit a higher exit hazard, consistent with the heavier lower tail of outcomes implied by risky experimentation. Second, conditional on survival, their relative sales paths subsequently outpace those of safe firms at later ages, consistent with selection on a heavier upper tail. These patterns are descriptive and not directly used for identification, but they support the validity of our model-consistent classification.

We then estimate wage equations with worker fixed effects—augmented, in increasingly demanding designs, by industry, industry×year, and firm fixed effects—and interact the experimentation indicator with local job-finding rates. The coefficient on this interaction asks whether wages at experimenting firms fall, relative to non-experimenting firms, as unemployment conditions improve. Identification comes from both cross-market differences and, most convincingly, from *within-firm* comparisons of workers employed by the same firm but residing in different commuting zones (and thus facing different outside options). Consistent with the mechanism, the interaction is negative and robust across specifications.

As an alternative test, we examine how the *young–mature* wage differential varies with local job-finding rates. The appeal of this test is that it avoids classification error—firm age is observed—though it is less sharp because it aggregates across heterogeneous young firms (some experimenting, others safe). The test is model-consistent: in the theory, the experimentation decision is made at entry, and only young firms are in the experimentation phase in which outcomes are unresolved and separation risk is higher. Once firms mature, experimentation uncertainty is resolved and separation risk is lower conditional on survival. While this dichotomy is starker in the model than in reality, the data support its spirit: Akcigit and Kerr (2018) document that innovative, exploratory activity related to the development of new products or services is disproportionately concentrated among younger firms. The model therefore predicts that higher job-finding rates lower the young–mature wage differential. Consistent with this prediction, the interaction of a young-firm dummy with the job-finding rate is negative and significant across specifications with worker fixed effects, industry and industry×year fixed effects, and, importantly, firm fixed effects—so that identification comes from within-firm differences across workers' commuting zones. We interpret these estimates as conditional correlations that corroborate, albeit indirectly, the main experimenting-vs.-safe result discussed above.

This negative correlation between local job-finding rates and the wage differential for employment at young (and, more sharply, experimenting) firms is at the heart of our theoretical mechanism. At the same time, the register-based evidence is correlational given that job finding rates are not randomly assigned. Hence, while the sign and robustness of the relationship are consistent with the unemployment channel of the model, the lack of purely exogenous variation in our setting prevents us from making definitive causal claims based on the microdata alone.

To isolate the worker-side mechanism more cleanly, we designed a survey experiment that elicits the wage differential workers require to accept employment at a higher-failure-risk young firm, and we experimentally vary unemployment duration. In a short module embedded in Danmarks Nationalbank's nationally-representative Survey of Consumers' Expectations, respondents first report their expected unemployment duration.[2] They are then randomly assigned to a vignette in which this

[2]This object is the survey analogue of the model's job-finding rate: under a constant job-finding hazard, expected unemployment duration satisfies $D = 1/f$, so higher expected duration corresponds

duration is hypothetically *halved* or *doubled*, and they compare two otherwise identical jobs that differ only in firm risk and growth potential: a stable firm with an annual closure rate of about 4% and an experimental young firm with an annual closure rate of about 20%. Respondents state whether they would switch only for higher pay, also at the same pay, or even for lower pay, and then quantify the required reservation premium (or acceptable discount).

Consistent with the theory, experimentally worsening unemployment conditions increases the required wage differential: Regressing the stated risky–safe wage differential on the randomized log change in unemployment duration yields a positive and statistically significant effect; a doubling of expected unemployment duration increases the required wage differential by about 3.6 percentage points. This experimental evidence strengthens the causal interpretation of the negative wage-differential–job-finding correlation uncovered in the Danish microdata, and we use the estimated semi-elasticity to discipline the strength of this mechanism in the calibration of the model.

Related literature This paper contributes to a growing literature that seeks to understand the macroeconomic importance of young firms, while recognizing that not all young firms are alike. A central insight from this literature is that high-growth young firms are the key drivers of job creation and aggregate productivity growth (Haltiwanger et al., 2016). However, many, if not most, new firms do not grow, nor do they aim to (Hurst and Pugsley, 2011), reflecting a divide between "transformational" and "subsistence" entrepreneurs (Schoar, 2010). Building on this, Sterk et al. (2021) show that differences in firm trajectories are largely predictable from the outset, pointing to an important role for ex-ante heterogeneity. Zooming in on the characteristics of founders, Akcigit et al. (2025) show that talent and education are key predictors of becoming a transformative entrepreneur. Our paper takes a different approach and contributes to this literature by uncovering a labor market origin for the prevalence of transformative, high-growth young firms in the economy. Notably, Kim (2025) shows that productive young firms with greater uncertainty pay higher wages than their mature counterparts, but does not further distinguish among different risk types of young firms. In contrast, we endogenize the choice between safe and risky—but high-potential—business models among new entrants in

to a lower job-finding rate.

a frictional labor market and show how labor market institutions, by shaping the value of unemployment, influence this selection margin.

Our paper also contributes to the vast literature on the implications of firm heterogeneity for aggregate productivity in the presence of labor market frictions.[3] In settings with firm heterogeneity, differences in aggregate productivity arise from (1) the underlying productivity distribution itself and (2) the allocation of resources across producers, given that distribution (Hsieh and Klenow, 2009). Hopenhayn and Rogerson (1993) show that firing costs reduce aggregate productivity by distorting resource allocation. Bilal et al. (2022) develop a tractable yet rich model of firm and worker dynamics with search and matching frictions and quantify the misallocation costs arising from such frictions. In contrast to this misallocation-focused perspective, our paper emphasizes how labor market institutions influence the productivity distribution itself through the unemployment channel and the endogenous choice of risky experimentation by entrants. Relatedly, Engbom (2022) also show that more fluid labor markets lead to higher aggregate productivity, but through a different mechanism—emphasizing job-to-job transitions and human capital accumulation.

Lastly, this paper contributes to the literature on experimentation in entrepreneurship (e.g., Kerr et al. (2014)). Existing work has largely emphasized how, from the point of view of a potential entrepreneur, post-failure insurance mechanisms—such as personal bankruptcy protection (Fan and White, 2003), outside employment options (Choi, 2017), job-protected leave (Gottlieb et al., 2022), future cash transfers (Bianchi and Bobba, 2013), or unemployment insurance (Hombert et al., 2020)—encourage individuals to undertake entrepreneurial risk. Our point of departure is to highlight that risk is shared: not only entrepreneurs, but also their employees, are exposed to downside uncertainty. We show that labor market institutions that make unemployment less costly can encourage entrepreneurial experimentation by lowering the wage compensation needed to attract talent, thereby fostering risk-taking through the wage-setting channel.

[3] See, for example, Buera et al. (2011) and Midrigan and Xu (2014) for financial frictions, and David et al. (2016) for information frictions.

2 The model

We build on Elsby and Michaels (2013)—a standard framework of heterogeneous multi–worker firms in a frictional labor market—and augment it in two respects. First, we adopt alternating–offer bargaining (AOB) instead of the Nash solution generalized to setups with decreasing returns. Second, at entry firms endogenously choose whether to undertake risky experimentation, which alters the subsequent productivity process and separation risk relative to the safe business model. In what follows, we describe the environment and labor–market structure, characterize firm and worker value functions, and derive the wage rule implied by AOB. The evolution of firm distributions and the labor–market clearing conditions are presented in Appendices A.1 and A.2, respectively.

2.1 The environment

Potential entrants can enter the market by paying a fixed entry cost, ψ_e. Upon entry, all firms start with the same permanent productivity level, z_e. With exogenous per-period probability φ, a young firm becomes mature, which we interpret as the resolution of uncertainty about its long-run productivity. Finally, in every period all firms are subject to persistent temporary productivity shocks, z_i, initialized at the same value for new entrants.

Upon entry, firms choose whether to operate a *safe* or *risky* business model. Safe firms do not experiment: their permanent productivity remains z_e even after becoming mature. Risky firms experiment: upon becoming mature, they draw a permanent productivity z_m from a distribution with support both below and above z_e, capturing that experimentation can lead to worse outcomes than the safe model, but also to better ones.

In the model, all entrants are ex-ante identical, so without additional structure, all firms would make the same choice of business model. To generate heterogeneity in choices and allow both safe and experimenting firms to coexist in equilibrium, we introduce idiosyncratic taste shocks. These shocks lead some firms to prefer the safe option, even when the expected pecuniary return to experimentation is higher.

Firms face decreasing returns to scale, and employ labor as the only factor of production. The labor market is frictional, so firms need to post vacancies in order to hire workers. We assume a unit measure of identical workers, who can be either employed or unemployed. Unemployed workers receive unemployment benefits b, while the employed receive a wage w, which is the outcome of an AOB protocol.

2.2 Timing

The sequence of events and actions within each period is the same for all ongoing firms, whether young or mature, and is depicted in Figure 1. At the start of each period, young firms draw a new permanent productivity level with probability φ, while mature firms retain their permanent productivity from the previous period. Both types of firms also receive a new temporary but persistent productivity shock. We denote the tuple of productivities as $\boldsymbol{z} = (z_p, z_i)$, where z_p is the permanent component—equal to z_e for young firms and z_m for mature firms—and z_i is the temporary component. Firms also carry over the number of workers from the previous period, n_{-1}, a relevant state variable due to hiring frictions.

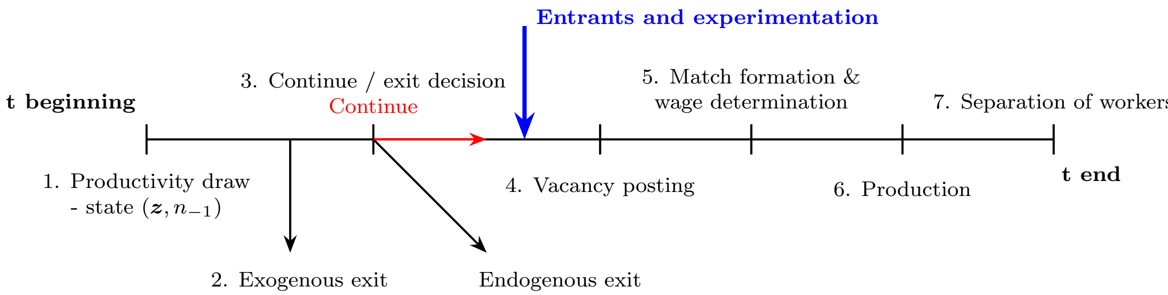
After the productivity draw, firms may exit the market exogenously at rate η. Those that do not exit exogenously must decide whether to remain in the market or exit voluntarily, depending on profitability. Subsequently, new firms enter the market, each beginning with one worker, permanent productivity z_e, and a temporary productivity drawn from the mean of the ergodic distribution of the temporary productivity process. Entrants then draw a taste shock and choose between operating a safe business or undertaking a riskier venture with higher upside potential.

Continuing firms—both new entrants and incumbents—then decide whether to post vacancies. If the optimal choice is to downsize, they post no vacancies and may lay off workers at no cost. At this stage, they also incur the fixed cost of operation, ψ_o. Next, hiring occurs, wages are negotiated, production takes place and wages are paid. Importantly, newly matched unemployed workers begin working in the same period. Finally, matches are dissolved through exogenous separations at rate ζ.

2.3 The frictional labor market

The labor market is governed by a standard matching function that brings together vacancies and unemployed job seekers. The rates at which job seekers find jobs, $f(\theta)$, and vacancies are filled, $q(\theta)$, depend solely on labor market tightness θ, defined as the ratio of vacancies to unemployment: $\theta = \frac{v}{u_0}$, where u_0 is the measure of unemployed workers at the time when firms post vacancies (stage 4 in Figure 1). That is, the

Figure 1: Timing



measure of job seekers that enter the definition of labor market tightness includes the workers who are fired because of endogenous exit (stage 3). Following convention, we assume a Cobb-Douglas matching function of the form $M(u_0, v) = mu_0^{\omega}v^{1-\omega}$, where M denotes the measure of matches per period, m captures matching efficiency, and ω is the elasticity of the matching function with respect to unemployment. This explicit functional form implies $f = m\theta^{1-\omega}$, $q = m\theta^{-\omega}$, with $df(\theta)/d\theta > 0$ and $dq(\theta)/d\theta < 0$.

2.4 Firms

2.4.1 Value functions

In this economy, we distinguish between three types of operating firms:

- **Safe firms ($\boldsymbol{s}$)** are those that chose not to experiment. Their permanent productivity is fixed at entry and remains at z_e throughout the firm's life. Because this value never changes, the firm's problem is the same whether it is considered a young or a mature firm. These firms face no risk of low productivity draws but also forgo the potential to become highly productive superstars.

- **Risky young firms ($\boldsymbol{ry}$)** are those that chose to experiment and have not yet matured. With probability φ, they will eventually draw a new permanent productivity level. Depending on the outcome, the firm may exit due to low productivity or continue as a mature firm—potentially becoming a superstar if the draw is very favorable.

- **Risky mature firms ($\boldsymbol{rm}$)** are those that previously chose risky experimentation and have since drawn their permanent productivity. These firms operate with the realized value going forward.

The value of a firm with productivity $\boldsymbol{z} = (z_p, z_i)$ and a number of workers n_{-1} at the beginning of the period is denoted by $V^j(\boldsymbol{z}, n_{-1})$, where $j \in \{s, ry, rm\}$. It is given by:

$$V^j(\boldsymbol{z}, n_{-1}) = (1-\eta)\max(V_c^j(\boldsymbol{z}, n_{-1}), 0), \tag{1}$$

where $V_c^j(\boldsymbol{z}, n_{-1})$ represents the continuation value of firms of type j, i.e., the value at the time where firms decide whether to continue operating or exit the market. The max function reflects the endogenous decision to continue or exit, with exit occurring when the value of continuing is zero or less and η is the probability of exogenous exit.

We now turn to define the continuation value of a firm of type j, denoted by $V_c^j((z_p, z_i), n_{-1})$, where the firm has permanent productivity z_p, temporary productivity z_i, and inherits n_{-1} workers from the previous period. Notice that safe and risky mature firms face the same optimization problem, conditional on their states, as both operate with known permanent productivity. The distinction lies in the source of that productivity: for safe firms, it is fixed at the entry level z_e, while for risky mature firms, it reflects the realized outcome of prior experimentation. Accordingly, we use the same value function expression for both types, indexing it by firm type to reflect differences in productivity and wage setting. For firms that are safe or risky-mature, this value function is:

$$\begin{aligned} V_c^j((z_p, z_i), n_{-1}) = \max_{n,v} & \, F((z_p, z_i), n) - w^j((z_p, z_i), n)n - c(v, n_{-1}) - \psi_o \\ & + \beta \mathbb{E}_{z_i'|z_i} V^j((z_p, z_i'), (1-\zeta)n), \quad \text{for } j \in \{s, rm\}, \end{aligned} \tag{2}$$
$$\text{subject to} \quad \Delta n \mathbb{1}_+ = (n - n_{-1})\mathbb{1}_+ = vq(\theta).$$

Here, n denotes the number of employees at the production stage—before the occurrence of exogenous worker separations. The indicator function $\mathbb{1}_+$ equals 1 when the firm hires new workers (i.e., when $\Delta n > 0$) and 0 otherwise. This ensures that vacancy posting costs are incurred only when the firm opens a positive measure of vacancies, while separations (firing) are costless. The function $F((z_p, z_i), n)$ denotes output given the firm's productivity and workforce. Wages $w^j((z_p, z_i), n)$ are determined through an AOB protocol, described in Section 2.6. The term $c(v, n_{-1})$ captures the cost of creating v vacancies when the firm starts the period with n_{-1} workers. The parameter $\psi_o > 0$ is a fixed operating cost, and $\beta \in (0, 1)$ is the discount factor. Finally, $\mathbb{E}_{z_i'|z_i}$ denotes the expected value over future temporary productivity

z_i', conditional on the current draw z_i. Workers separate exogenously at rate ζ.

For *risky young firms*, the expression differs from the previous cases due to the possibility of transitioning into maturity with probability φ. The continuation value includes an additional expectation over permanent productivity draws, as shown below:

$$
\begin{aligned}
V_c^{ry}((z_e, z_i), n_{-1}) = \max_{n,v} & \, F((z_e, z_i), n) - w^{ry}((z_e, z_i), n)n - c(v, n_{-1}) - \psi_o \\
& + \beta \mathbb{E}_{z_i'|z_i} \left[(1-\varphi) V^{ry}((z_e, z_i'), (1-\zeta)n) + \varphi \mathbb{E}_{z_m} V^{rm}((z_m, z_i'), (1-\zeta)n) \right], \\
\text{subject to} \quad & \Delta n \mathbb{1}_+ = (n - n_{-1}) \mathbb{1}_+ = vq(\theta),
\end{aligned}
\tag{3}
$$

where $\mathbb{E}_{z_m}$ denotes the expectation over the permanent productivity draws.

2.4.2 Endogenous experimentation and entry

New entrants compare the continuation values of the safe and risky business models to decide which path to pursue. We assume the presence of taste shocks, denoted by ϵ, associated with choosing the safe option. These shocks serve as a reduced-form representation of non-pecuniary motives for running a business (Hurst and Pugsley (2011)).

Let $\mathcal{E}^s \equiv V_c^s((z_e, \mu_{z_i}), 1)$ and $\mathcal{E}^{ry} \equiv V_c^{ry}((z_e, \mu_{z_i}), 1)$ denote the continuation values at entry for firms choosing the safe and risky business models, respectively. Entrants begin with one worker and a temporary productivity level equal to the mean of the ergodic distribution of the temporary productivity process, denoted by μ_{z_i}. The expected value of entry, $\mathcal{E}$, is then given by:

$$
\mathcal{E} = \mathbb{E}_\epsilon \left[\max \left(\mathcal{E}^s + \epsilon, \mathcal{E}^{ry} - c_\sigma \right) \right], \tag{4}
$$

where c_σ is the cost associated with selecting the risky option, and $\mathbb{E}_\epsilon$ denotes the expectation over the idiosyncratic taste shocks ϵ.

We further assume that the taste shocks ϵ follow a Gumbel distribution with scale parameter σ_σ, and a location parameter normalized such that the expectation is unaffected by the existence of taste shocks, i.e., $E_\epsilon[\max(\epsilon, 0)] = 0$. Under this assumption, the value of entry simplifies to:

$$
\mathcal{E} = \sigma_\sigma \log \left(\exp \left(\frac{\mathcal{E}^s}{\sigma_\sigma} \right) + \exp \left(\frac{\mathcal{E}^{ry} - c_\sigma}{\sigma_\sigma} \right) \right), \tag{5}
$$

and the share of entrants that choose risky experimentation is given by:

$$P(R) = \frac{\exp\left(\frac{\mathcal{E}^{ry}-c_\sigma}{\sigma_\sigma}\right)}{\exp\left(\frac{\mathcal{E}^{ry}-c_\sigma}{\sigma_\sigma}\right)+\exp\left(\frac{\mathcal{E}^{s}}{\sigma_\sigma}\right)}, \tag{6}$$

which is increasing in $\mathcal{E}^{ry}$.

Since entry is endogenous, equilibrium requires that the expected value of entry equals its fixed cost: $\mathcal{E} = \psi_e$.

2.4.3 Optimality conditions for the firm's problems

Let's derive the first order conditions for the firm's problem in equations (2) and (3). First, define the marginal value of a worker to a safe or risky mature firm as:[4]

$$J^j(\boldsymbol{z}, n) = F_n(\boldsymbol{z}, n) + \beta\mathbb{E}_{z_i'|z_i}\left[\frac{\partial V^j(\boldsymbol{z},(1-\zeta)n)}{\partial n}\right] - w^j(\boldsymbol{z}, n) \quad \text{for } j \in \{s, rm\}. \tag{7}$$

In turn, the marginal value of a worker to a risky young firm takes the form:

$$\begin{aligned} J^{ry}(\boldsymbol{z}, n) = F_n(\boldsymbol{z}, n) + \beta\mathbb{E}_{z_i'|z_i}\Big[(1-\varphi)\frac{\partial V^{ry}(\boldsymbol{z},(1-\zeta)n)}{\partial n} \\ + \varphi\mathbb{E}_{z_m}\frac{\partial V^{rm}(\boldsymbol{z},(1-\zeta)n)}{\partial n}\Big] - w^{ry}(\boldsymbol{z}, n), \end{aligned} \tag{8}$$

Imposing optimality, the first order condition for vacancy creation implies that marginal returns and costs of hiring are equalized:

$$\frac{c_v(v, n_{-1})}{q(\theta)}\mathbb{1}_{+} = J^i(\boldsymbol{z}, n), \quad i \in \{s, rm, ry\}. \tag{9}$$

2.5 Workers

A worker who starts the period unemployed and remains unmatched receives unemployment benefits b at the end of the period and we assume workers have linear utility. The corresponding value of unemployment, denoted by U, is:

$$U = b + \beta\mathbb{E}_v\left[(1-f)U' + fE^j(\boldsymbol{z}', n')\right], \tag{10}$$

where the expectation $\mathbb{E}_v$ is taken over the distribution of vacancies across $(\boldsymbol{z}', n')$ and over firm types $j \in \{s, rm, ry\}$.

Let E denote the value of employment to a worker at the production stage. For

[4] To maintain tractability, we assume that the firm does not take into account the impact of its hiring decision on the negotiated wage bill. As a result, the term $w_n n$ does not appear in equations (7) and (8).

a worker employed at a safe or risky mature firm, this value is:

$$E^j(\boldsymbol{z}, n) = w^j(\boldsymbol{z}, n) + \beta \mathbb{E}_{z_i'|z_i}\Big[p_\varsigma^j(\boldsymbol{z}, (1-\zeta)n) \cdot U' + \big(1 - p_\varsigma^j(\boldsymbol{z}, (1-\zeta)n)\big) \cdot E^j(\boldsymbol{z}, n^{j,*}(\boldsymbol{z}, (1-\zeta)n))\Big], \quad \text{for } j \in \{s, rm\} \quad (11)$$

where $p_\varsigma^j(\boldsymbol{z}, (1-\zeta)n)$ denotes the endogenous separation probability, which accounts for all sources of job loss—exogenous separations, firm exits (both exogenous and endogenous), and layoffs. The term $n^{j,*}(\boldsymbol{z}, (1-\zeta)n)$ represents the firm's optimal labor demand in the next period, conditional on survival and after accounting for separations.[5]

In turn, for a worker employed in a risky young firm, the value function includes both the possibility of the firm remaining young and transitioning into maturity, with corresponding adjustments to future employment values and separation risk:

$$\begin{aligned} E^{ry}(\boldsymbol{z}, n) = w^{ry}(\boldsymbol{z}, n) + \beta \mathbb{E}_{z_i'|z_i}\Big[&(1-\varphi)\Big(p_\varsigma^{ry}(\boldsymbol{z}, (1-\zeta)n) \cdot U' \\ &+ \big(1 - p_\varsigma^{ry}(\boldsymbol{z}, (1-\zeta)n)\big) \cdot E^{ry}(\boldsymbol{z}, n^{ry,*}(\boldsymbol{z}, (1-\zeta)n))\Big) \\ &+ \varphi \mathbb{E}_{z_m}\Big(p_\varsigma^{rm}(\boldsymbol{z}, (1-\zeta)n) \cdot U' \\ &+ \big(1 - p_\varsigma^{rm}(\boldsymbol{z}, (1-\zeta)n)\big) \cdot E^{rm}(\boldsymbol{z}, n^{rm,*}(\boldsymbol{z}, (1-\zeta)n))\Big)\Big]. \end{aligned} \quad (12)$$

Here, the expectation over z_m reflects the uncertainty over the firm's permanent productivity upon transition.

For use in wage determination, and following Hall and Milgrom (2008), we decompose the value of employment, E^j, into two components: the present discounted value of wages conditional on the match continuing, denoted by W^j, and the *subsequent career value*, C^j, which captures the continuation value in states where the worker becomes unemployed, as defined by Hall and Milgrom (2008). Formally:

$$E^j(\boldsymbol{z}, n) = W^j(\boldsymbol{z}, n) + C^j(\boldsymbol{z}, n) \quad \text{for } j \in \{s, rm, ry\}. \quad (13)$$

[5]Formally, the endogenous probability of survival is defined as:

$$1 - p_\varsigma^j(\boldsymbol{z}, (1-\zeta)n) = (1-\zeta) \cdot (1-\eta) \cdot \big(1 - p_x^j(\boldsymbol{z}, (1-\zeta)n)\big) \cdot \min\left(\frac{n^{j,*}(\boldsymbol{z}, (1-\zeta)n)}{(1-\zeta)n}, 1\right),$$

where a worker continues the match if: they are not exogenously separated $(1-\zeta)$; the firm does not exit exogenously $(1-\eta)$ or endogenously $(1-p_x^j)$; and they are not laid off. The last term—the *layoff condition*—ensures that if the firm downsizes, each worker faces a uniform retention probability equal to the ratio of next period's workforce to the number of continuing workers, i.e., $\min\left(\frac{n^{j,*}}{(1-\zeta)n}, 1\right)$.

For workers employed in safe or risky mature firms, i.e., for $j \in \{s, rm\}$, the present discounted value of wages is:

$$W^j(\boldsymbol{z}, n) = w^j(\boldsymbol{z}, n) + \beta \mathbb{E}_{z_i'|z_i} \Bigg[(1 - p_\varsigma^j(\boldsymbol{z}, (1-\zeta)n)) W^j(\boldsymbol{z}, n^{j,*}(\boldsymbol{z}, (1-\zeta)n)) \Bigg], \quad (14)$$

and the subsequent career value is:

$$\begin{aligned} C^j(\boldsymbol{z}, n) = \beta \mathbb{E}_{z_i'|z_i} \Bigg[\Big(& p_\varsigma^j(\boldsymbol{z}, (1-\zeta)n) U' \\ & + (1 - p_\varsigma^j(\boldsymbol{z}, (1-\zeta)n)) C^j(\boldsymbol{z}, n^{j,*}(\boldsymbol{z}, (1-\zeta)n)) \Big) \Bigg]. \end{aligned} \quad (15)$$

Similarly, for workers employed at risky young firms, the present discounted value of wages, W^{ry}, and the subsequent career value, C^{ry}, are:

$$\begin{aligned} W^{ry}(\boldsymbol{z}, n) = w^{ry}(\boldsymbol{z}, n) + \beta \mathbb{E}_{z_i'|z_i} \Bigg[& (1-\varphi) \cdot \big(1 - p_\varsigma^{ry}(\boldsymbol{z}, (1-\zeta)n)\big) W^{ry}(\boldsymbol{z}, n^{ry,*}(\boldsymbol{z}, (1-\zeta)n)) \\ & + \varphi \, \mathbb{E}_{z_m} \big(1 - p_\varsigma^{rm}(\boldsymbol{z}, (1-\zeta)n)\big) W^{rm}(\boldsymbol{z}, n^{rm,*}(\boldsymbol{z}, (1-\zeta)n)) \Bigg], \end{aligned} \quad (16)$$

$$\begin{aligned} C^{ry}(\boldsymbol{z}, n) = \beta \mathbb{E}_{z_i'|z_i} \Bigg[& (1-\varphi) \cdot \Big(p_\varsigma^{ry}(\boldsymbol{z}, (1-\zeta)n) \cdot U' \\ & + \big(1 - p_\varsigma^{ry}(\boldsymbol{z}, (1-\zeta)n)\big) C^{ry}(\boldsymbol{z}, n^{ry,*}(\boldsymbol{z}, (1-\zeta)n)) \Big) \\ & + \varphi \, \mathbb{E}_{z_p} \Big(p_\varsigma^{rm}(\boldsymbol{z}, (1-\zeta)n) \cdot U' \\ & + \big(1 - p_\varsigma^{rm}(\boldsymbol{z}, (1-\zeta)n)\big) C^{rm}(\boldsymbol{z}, n^{rm,*}(\boldsymbol{z}, (1-\zeta)n)) \Big) \Bigg]. \end{aligned} \quad (17)$$

Since the career value of workers in risky young firms places greater weight on unemployment—due to their higher likelihood of exit or layoff under our calibration—a higher unemployment value U has a relatively larger impact on these workers than on those in safe or mature risky firms.

2.6 Wage determination

Wages are negotiated according to the alternating offer bargaining protocol (AOB), which builds on the non-cooperative bargaining model by Binmore et al. (1986). This protocol modifies the traditional Nash bargaining model by replacing unrealistic threat points with credible alternatives. Specifically, it distinguishes between outside options and threat points during bargaining. In contrast, in the standard Nash bargaining model, outside options and threat points are the same. For workers, the outside option is unemployment, while for firms, it is a zero value. Rather than assuming that job-seekers and employers will terminate negotiations and pursue outside options when they disagree, the AOB protocol allows both parties to alternate offers until an agreement is reached. The model emphasizes the costs of delay, rather than outside options, as the key determinant of bargaining outcomes. Both parties face credible threats: the employer incurs a cost of delay, while the worker receives a smaller value if they delay the agreement, as future rewards are discounted.

This bargaining protocol offers several advantages over standard Nash bargaining that are central for our purposes. First, it disciplines the pass-through from the value of unemployment into negotiated wages: Jäger et al. (2020) show that Nash bargaining implies counterfactually large wage elasticities with respect to unemployment benefits, whereas AOB generates empirically plausible responses. This feature matters quantitatively in our setting because it governs how changes in the value of unemployment translate into average labor costs, and hence into entry. Second, AOB allows the wage response to unemployment conditions to depend on separation risk: unlike Nash, it delivers separation-rate heterogeneity in the sensitivity of flow wages to job-finding conditions, in line with our evidence (see Appendix A.3 and Table 2; we return to this comparison below). Finally, AOB has been shown to improve the performance of search-and-matching models along additional macro dimensions (e.g. Hall and Milgrom, 2008; Christiano et al., 2016).

It is assumed that each employed worker engages in individual negotiations with their employer to determine the current wage. These negotiations are bilateral, with each worker-firm pair treating the outcomes of other wage bargains in period t as fixed. In our model, periods t represent quarters, with bargaining taking place across an infinite number of subperiods. The process begins with the firm making a wage offer at the start of the first subperiod. If the worker rejects it, the firm presents another offer at the start of each subsequent odd-numbered subperiod. Conversely, the worker makes counteroffers during even-numbered subperiods if all prior offers have been declined. During any subperiod, the recipient of an offer can choose to accept or reject it. If an offer is rejected, the recipient has two options: either declare an end to negotiations or prepare a counteroffer for the next subperiod. In the latter case, there is a probability, $\delta_b < 1$, that the bargaining process collapses.

The total value of a match is given by $J^j(\boldsymbol{z},n)+W^j(\boldsymbol{z},n)+C^j(\boldsymbol{z},n) = P^j(\boldsymbol{z},n)+C^j(\boldsymbol{z},n)$ for $j \in \{s, rm, ry\}$, where $P^j(\boldsymbol{z},n) = J^j(\boldsymbol{z},n) + W^j(\boldsymbol{z},n)$ represents the value of the match to the firm before wages are paid. Firms and workers bargain over the present discounted sum of wages, $W^j(\boldsymbol{z},n)$.

We denote the wage offer made by firms and workers as $W^j(\boldsymbol{z},n)$ and $W_k^j(\boldsymbol{z},n)$ for $j \in \{s, ry, rm\}$, respectively. The condition that makes a worker indifferent between accepting and rejecting the firm's offer is:

$$\begin{aligned} E^j(\boldsymbol{z},n) &= \delta_b U + (1-\delta_b)\left(z_b + \beta_b E_k^j(\boldsymbol{z},n)\right), \\ \Leftrightarrow W^j(\boldsymbol{z},n) + C^j(\boldsymbol{z},n) &= \delta_b U + (1-\delta_b)\left(z_b + \beta_b(W_k^j(\boldsymbol{z},n) + C^j(\boldsymbol{z},n))\right), \end{aligned} \tag{18}$$

where $E^j(\boldsymbol{z},n)$ and $E_k^j(\boldsymbol{z},n)$ are the values to a worker in a firm of type j with states $(\boldsymbol{z},n)$ when the present discounted value of wages are $W^j(\boldsymbol{z},n)$ and $W_k^j(\boldsymbol{z},n)$, respectively, and the expression in the second row follows from Eq.(13). Note that z_b is a flow value to a worker in the next sub-period when the bargaining is not settled over the current sub-period. β_b is the discount rate used within bargaining subperiods. Similarly, firms are indifferent between accepting and rejecting the worker's offer when:

$$\begin{aligned} J_k^j(\boldsymbol{z},n) &= (1-\delta_b)\left(-\gamma_b + \beta_b J^j(\boldsymbol{z},n)\right), \\ \Leftrightarrow P^j(\boldsymbol{z},n) - W_k^j(\boldsymbol{z},n) &= (1-\delta_b)\left(-\gamma_b + \beta_b(P^j(\boldsymbol{z},n) - W^j(\boldsymbol{z},n))\right), \end{aligned} \tag{19}$$

where γ_b denotes the cost to the firm of delaying a bargaining agreement, and $J^j(\boldsymbol{z},n)$ and $J_k^j(\boldsymbol{z},n)$ are the values of a job to the firm when the present discounted wages are $W^j(\boldsymbol{z},n)$ and $W_k^j(\boldsymbol{z},n)$, respectively.

Combining (18) and (19) leads to the following closed-form solution for $W^j(\boldsymbol{z},n)$:

$$\begin{aligned} W^j(\boldsymbol{z},n) = \frac{1}{1-\beta_b^2(1-\delta_b)^2}\Big[&(1-\delta_b)z_b + (1-\delta_b)^2\beta_b\gamma_b + \delta_b U \\ &+ (1-\delta_b)\beta_b(1-\beta_b(1-\delta_b))P^j(\boldsymbol{z},n) - (1-\beta_b(1-\delta_b))C^j(\boldsymbol{z},n)\Big]. \end{aligned} \tag{20}$$

Lastly, we derive the flow wage $w^j(\boldsymbol{z},n)$ that is consistent with (14) and (20).[6]

2.7 Discussion: The unemployment channel

This section highlights the model's core propagation mechanism: a change in the job-finding rate induced by labor market institutions affects the value of unemployment,

[6]Note that outside the steady state, there exists an infinite sequence of flow wages consistent with $W^j(\boldsymbol{z},n)$. However, in the steady state—the focus of our analysis—the flow wage $w^j(\boldsymbol{z},n)$ can be determined by (14) and (20).

which feeds into the wage bargaining process and alters the relative wages offered by risky young firms compared to safer firms. These wage differentials, in turn, shape firms' incentives to engage in risky experimentation. We illustrate this mechanism in the following steps:

1. An increase in f raises the value of unemployment U (Eq. (10)), since $E^j(\boldsymbol{z}', n') > U$; otherwise, workers would receive no surplus from the match.

2. For a given wage, an increase in U affects the career value of workers, C^j, differently in risky young firms compared to safe firms. Risky young firms have a higher likelihood of match destruction coming from either higher exit rates or higher endogenous layoffs. As a result, an increase in U raises the career value more significantly in risky young firms than in safe or risky mature firms. Comparing the effects between risky young firms and safe firms, in Eq. (15) and (17), under the assumption of a stationary equilibrium where $U' = U$, one can see that:
$$\frac{\partial C^{ry}(\boldsymbol{z}, n)}{\partial U} > \frac{\partial C^{s}(\boldsymbol{z}, n)}{\partial U},$$
$$\text{when } (1-\varphi)p_{\varsigma}^{ry}(\boldsymbol{z}, (1-\zeta)n) + \varphi \mathbb{E}_{z_m} p_{\varsigma}^{rm}(\boldsymbol{z}, (1-\zeta)n) > p_{\varsigma}^{s}(\boldsymbol{z}, (1-\zeta)n), \quad (21)$$
i.e., the expected one–period–ahead separation probability at a risky young firm—averaging the risk while young and upon transition to maturity—exceeds that at a safe firm with the same current state.

3. From the wage equation (20), note that $\frac{\partial W^j}{\partial C^j} < 0$ is independent of the firm type $j \in \{s, rm, ry\}$. Consequently, the larger increase in C^{ry} relative to C^s induced by an increase in the job finding rate leads to a decrease in present-value wages in risky young firms relative to safe firms, i.e., $\frac{d(W^{ry} - W^s)}{df} < 0$.

4. Due to lower present-value wages at risky young firms, the value of choosing the risky experiment increases relative to the safe route. As a result, the probability of choosing risky experimentation conditional on entry, $P(R)$, rises according to equation (6).

Intuitively, the negotiated present-value wage in equation (20) is shaped by two distinct effects of the value of unemployment. First, the value of unemployment enters *directly* as the worker's fallback payoff if bargaining breaks down with probability δ_b, which pushes the wage up. Second, the value of unemployment enters *indirectly* through the worker's career value, C, i.e., the employment-continuation value associated with states in which the worker becomes unemployed. In equation (20) this channel loads with a negative sign. To see why, remember that $E = W + C$. In equilibrium, the value of employment accepted by the worker must equal the value of delaying agreement; holding the value of delay fixed, a higher C raises the value of employment E, so a lower present value of wages W is sufficient to make the worker indifferent between accepting and delaying. Crucially, this continuation value rises more steeply in firms with higher separation risk, as the likelihood of transitioning into unemployment is greater. As a result, a higher career value reduces negotiated wages more at risky firms than at safe firms, reducing the risky–safe wage differential.

AOB versus Nash. We adopt alternating–offer bargaining (AOB) instead of Nash bargaining for two reasons. First, the two frameworks deliver different predictions for how *current* (flow) wages respond to job-finding conditions across matches with different separation risk. In a standard Diamond–Mortensen–Pissarides setting, Nash bargaining implies that the equilibrium flow wage is independent of the match separation rate s; consequently, changes in the job-finding rate f shift flow wages without any interaction with separation risk, i.e. $\partial^2 w^{\text{Nash}}/(\partial s\, \partial f) = 0$.[7] Under AOB, by contrast, the equilibrium flow wage depends on s and the interaction is strictly negative, $\partial^2 w^{\text{AOB}}/(\partial s\, \partial f) < 0$ (see Proposition 1 in Appendix A.3). This negative cross-partial implies that an improvement in job-finding conditions lowers flow wages in high-separation (riskier) firms relative to low-separation (safer) firms, so the risky–safe wage differential declines as job-finding improves. Table 2 confirms that this separation-rate dependence of the wage response carries over to *current* wages in our calibrated model, and in Section 5 we find that the risky–safe wage differential varies with the job-finding rate in the direction implied by AOB, whereas Nash implies no such heterogeneity.

Second, Nash bargaining implies a counterfactually large pass-through from the value of unemployment (and hence unemployment benefits) into average wages. Micro

[7]Proposition 2 in Appendix A.3 shows that this Nash invariance also extends to the case of risk-averse workers. Intuitively, the separation rate affects the *level* of total match surplus by changing expected match duration. Under Nash bargaining, however, the negotiated wage is pinned down by a proportional split of the surplus: it is chosen to deliver a fixed share of surplus to the worker (and the complement to the firm), independently of how large the surplus is. Hence variation in separation risk does not generate separation-rate dependence in the flow-wage response to job-finding conditions.

evidence in Jäger et al. (2020) finds substantially smaller wage responses to changes in unemployment benefits than the Nash benchmark implies. This distinction matters quantitatively in our setting, because excessive wage pass-through would raise average labor costs and, all else equal, depress entry and job finding rates.

On-the-job search and employment-to-employment flows. For simplicity, our matching block features only unemployment-to-employment transitions: vacancies are matched with unemployed job seekers, and we abstract from on-the-job search and employer-to-employer (EE) mobility. This modelling choice is not meant to suggest that EE flows are unimportant empirically; rather, we omit them to keep the environment parsimonious and to isolate the channel of interest.

Incorporating EE flows in a heterogeneous multi-worker firm model is challenging because standard job-ladder wage-setting typically implies within-firm wage dispersion. Under sequential-auction bargaining ‘a la Postel-Vinay and Robin (2002), an incumbent's wage is pinned down by the best outside offer and the incumbent firm's willingness to match. With heterogeneous poachers, otherwise identical workers in the same firm can receive different outside offers and therefore earn different wages. In a multi-worker setting, this forces one to track the endogenous within-firm wage distribution as part of the firm's state, which quickly becomes computationally infeasible. Bilal et al. (2022) maintain tractability by solving the model in terms of joint surplus (rather than wages), so wages can be left indeterminate without affecting allocations; while powerful, this strategy is not well suited for our purposes because our mechanism hinges on how negotiated wages respond to changes in unemployment conditions across firm types.

A tractable alternative is provided by the timing structure in Elsby and Gottfries (2021), where workers decide whether to move to a poaching vacancy *before* wages are negotiated, based on the *expected* AOB wage at the destination firm. Wages are then set *ex post* within the firm by the standard AOB condition that equates the value of employment to the value of delay, delivering a common wage given the firm's state. Because the post-move outside option is effectively unemployment, this extension would remain tractable in our multi-worker setting and would preserve our qualitative mechanism: job-finding conditions continue to tilt wage responses across firms with different separation risk.

3 Mapping the model to data

Functional forms We assume a standard decreasing returns to scale technology, $F((z_p, z_i), n) = z_p z_i n^\alpha$, $\alpha < 1$. Experimenting entrants draw permanent productivity from a Pareto distribution with scale parameter ξ and mean normalized to one. The persistent temporary productivity z_i follows a standard AR(1) process, i.e., $\log(z_i') = \rho_z \log(z_i) + \epsilon_z$, $\epsilon_z \sim N(0, \sigma_z^2)$. The vacancy cost function is defined as $c(v, n_{-1}) = \chi_0(\frac{v}{n_{-1}})^{\chi_1} v$, following Bilal et al. (2022).

Calibration strategy We divide the model parameters into two groups: those set externally, and those internally calibrated to match informative moments and identify key parameters. The model is calibrated to the Danish economy, assuming that one period corresponds to a quarter. Wherever possible, we use data from Danish National Accounts or microdata from the Danish administrative registers. We use estimates from the literature based on other economies only when equivalent analysis for Denmark is unavailable.

Externally Set Parameters The discount factor β implies an annual interest rate of 4%. The returns to scale parameter α is set to 0.64, estimated by Cooper et al. (2004) using a structural labor demand model. We set the matching efficiency to 0.48 to target a quarterly job-finding rate of 0.48 in Denmark, assuming a normalized market tightness of 1 (Darougheh et al. (2024)). The elasticity in the Cobb-Douglas matching function is set to 0.5, which is standard in the literature (Petrongolo and Pissarides (2001)). We set the replacement ratio b to 0.297 to match the observed ratio of unemployment to employment income in Denmark (Darougheh et al. (2024)). We set the quarterly probability φ of a young firm transitioning to maturity to 1/12, in line with the three-year definition of young firms adopted in the empirical analysis. The persistence of the temporary productivity process is set to 0.659, following Khan and Thomas (2013). Finally, the scale parameter χ_0 in the matching function is normalized to one.

Internally Calibrated Parameters The remaining parameters are set to match informative moments from the data. Unless otherwise noted, we compute moments using establishment-level data from Statistics Denmark (IDAS), the Danish equivalent of the U.S. Longitudinal Business Database (LBD). First, the shape parameter ξ of the permanent productivity distribution is calibrated to match the employment share of the top 1% of firms, ranked by employment size. The standard deviation of temporary productivity shocks, σ_z, is set to match that of log employment growth. The curvature parameter of the vacancy cost function, χ_1, is calibrated to match the employment-weighted average job creation rate. The exogenous exit probability η and operating cost ψ_o are calibrated to match the overall and young-firm exit rates, respectively. The relative size of mature to young firms is used to identify the productivity of new entrants, z_e. Finally, the worker's exogenous separation rate, ζ, is set to match the unemployment rate.

Four parameters—δ_b, β_b, c_σ, and σ_σ—warrant special attention, as they are central to our mechanism. The bargaining parameters (δ_b, β_b) discipline wage setting through equation (20), while the experimentation parameters $(c_\sigma, \sigma_\sigma)$ govern the experimentation decision through equation (6).

First, the disruption probability in bargaining, δ_b, is calibrated to match the *average* wage response to changes in unemployment benefits; a higher δ_b increases the sensitivity of the average wage to changes in the value of unemployment. Jäger et al. (2020) provide careful estimates of the average wage response to a one-dollar increase in unemployment benefits (dw/db), using multiple unemployment insurance reforms in Austria. They find that the wage response to benefits is surprisingly small, rejecting dw/db values above 0.03. We therefore use 0.03 as the target for this moment. Second, the parameter β_b is particularly relevant for our analysis. Since β_b governs discounting during bargaining, it determines the cost of delay and therefore workers' wage acceptance decisions. Quantitatively, β_b is the key determinant of how the safe–risky wage *differential* among young firms responds to job-finding conditions—the main elasticity underlying our mechanism. We discipline β_b by choosing it to match the semi-elasticity of the safe–risky wage differential with respect to the job-finding rate estimated in our survey experiment (Section 6).[8]

Turning to the second set of parameters, we calibrate the cost of risky experimen-

[8]The survey estimate identifies a partial-equilibrium effect of job finding on wage-setting: holding firm-side objects fixed, a higher job-finding rate shifts the wage that makes workers indifferent between accepting and rejecting an offer. In the model, comparing stationary equilibria in which job-finding rates differ (e.g., due to changes in vacancy-posting costs) could in principle add general-equilibrium feedback through changes in market tightness that affect firm surplus (the P term in equation 20). However, Table 2 shows that wage differentials respond to the worker-side outside option U, not to demand-side general-equilibrium forces, so we abstract from this feedback when calibrating β_b.

tation, c_σ, to match the empirical share of non-experimenting entrepreneurs. Hurst and Pugsley (2011) document that roughly one-third to one-half of entrepreneurs report no intention to introduce new products or services. We therefore set a target non-experimenting share of 50% and choose c_σ so that the model reproduces it.

Lastly, we calibrate σ_σ, the scale (dispersion) of the non-pecuniary taste shocks that tilt entrepreneurs toward the safe option. In equation (6), σ_σ governs the elasticity of the experimentation probability $P(R)$ with respect to the pecuniary value of experimentation, $\mathcal{E}^{ry}$. We discipline σ_σ by matching the coefficient from a regression of the *young-firm share* on the job-finding rate across Danish regions.[9] This moment is informative because, in the model, the young-firm share is tightly linked to the share of experimenting young firms: more experimentation raises the endogenous exit hazard, increasing firm turnover and mechanically raising the fraction of firms that are young. A larger σ_σ implies a more dispersed distribution of non-pecuniary taste shocks, so experimentation choices are driven primarily by idiosyncratic motives rather than by changes in relative values induced by wages. In that case, changes in job-finding rates—which affect $\mathcal{E}^{ry}$ through the safe–risky wage differential—have little effect on experimentation, and therefore little effect on firm turnover and the young-firm share. Hence, the regional sensitivity of young-firm shares to job-finding conditions pins down σ_σ.

Table 1 summarizes the model parameters and their corresponding data targets. Overall, the calibrated model fits the target moments well. One exception is the regression coefficient of the young firm share on the job-finding rate, which the model underpredicts. In principle, this coefficient could be increased by lowering σ_σ. However, doing so would raise the model-implied value of dw/db, which is already calibrated to the upper bound of the estimates in Jäger et al. (2020), creating tension in moment targeting. We therefore prioritize matching dw/db and keep σ_σ unchanged. As a result, the quantitative effects reported in the next section should be seen as a lower bound: reducing σ_σ would amplify the response of risky experimentation and

[9] Details on the construction of these variables are provided in Section 5. A more direct approach would be to regress the *local* share of experimenting young firms on the local job-finding rate. We cannot implement this because our estimates of the experimentation indicator are defined at the *firm* level, whereas geographic assignment is naturally done at the *establishment* level. Establishments can be mapped cleanly to local labor markets, but multi-establishment firms operate across multiple areas, so a firm-level experimentation classification cannot be meaningfully attributed to a single location. Hence, while the young-firm regressions can be carried out at the establishment level, an analogous regression for the share of experimenters is not feasible.

Table 1: Parameters and targeted moments

Parameter		Value	Moment	Model	Data
			A. Externally set		
β	Discount rate	0.99	4% annual interest rate		
α	Returns to scale	0.64	Cooper et al. (2004)		
m	Matching efficiency	0.48	Darougheh et al. (2024)		
ω	Matching elasticity	0.5	Petrongolo and Pissarides (2001)		
b	Replacement ratio	0.297	Darougheh et al. (2024)		
φ	Prob. of being mature	1/12	3 years duration as young firms		
ρ_z	Persistence of temp. prod.	0.659	Khan and Thomas (2013)		
χ_0	Matching fn scale param.	1.00	Normalization		
			B. Internally calibrated		
ξ	Shape of perm. prod. dist.	2.4	Emp. share of top 1%	0.272	0.298
σ_z	SD of temp. prod. shocks	0.18	SD of log emp growth	0.062	0.113
χ_1	Vacancy cost curvature	1.2	avg. JC rate, weighted	0.040	0.040
η	Exogenous exit rate	0.023	Exit rate	0.033	0.033
ψ_o	Operating cost	0.6	Exit rate (young firms)	0.054	0.067
z_e	Entrants' productivity	1.419	Rel. size of mature to young firms	2.321	2.462
ζ	Worker separation rate	0.023	Unemployment rate	0.055	0.044
c_b	Constant in bargaining	0.007	Labor share	0.609	0.594
δ_b	Bargaining disruption prob.	6.55×10^{-4}	dw/db (Jäger et al. (2020))	0.031	0.030
β_b	Discount rate (bargaining)	0.9999	survey estimate of $\hat{b}$ in eq.(26)	5.548	5.134
c_σ	Risky-experimenation cost	7.47	Share of non-experimenting firms (Hurst and Pugsley (2011))	0.497	0.500
σ_σ	Scale of safe taste shocks	0.28	Reg. coeff. of young firm shares to UE	0.295	0.763

Notes: Worker payoff, z_b, and firm cost, γ_b, in bargaining are aggregated into a constant c_b where $c_b := (1-\delta_b)z_b + (1-\delta_b)^2\beta_b\gamma_b$ as we do not need these parameters separately.

the resulting productivity gains.

4 Model experiments

In this section, we investigate the effects of a reduction in hiring costs. This approach—following Engbom (2022)—serves as a reduced-form method for capturing the influence of labor market institutions that have been shown to hinder labor market flows, such as employment protection legislation, business regulations, and labor taxes (Hopenhayn and Rogerson (1993), Pries and Rogerson (2005)). This modeling strategy aligns with the 'indirect' approach in the misallocation literature, where institutional inefficiencies are often represented as wedges, enabling analytical tractability through deliberate abstraction (Hsieh and Klenow (2009)). Importantly, our goal

Table 2: Effects of Lower Hiring Costs on Wages, Experimentation, and Young Firms

	Baseline	Low χ_0	Δ	Low χ_0, fixed U	Δ_U
Young Firm Wage (Safe)	0.695	0.697	0.200	0.695	-0.001
Young Firm Wage (Risky)	0.711	0.705	-0.850	0.711	-0.001
Young Firm Wage	0.703	0.702	-0.195	0.703	-0.001
Mature Firm Wage	0.661	0.664	0.459	0.661	-0.001
Share of Experimentation	0.497	0.595	9.727	0.497	0.008
Entrants Mass	0.009	0.009	2.285	0.009	1.651
Young Firm Share	0.318	0.348	2.985	0.319	0.002
Young Firm Employment Share	0.168	0.169	0.163	0.168	0.000

Notes: This table shows how lower hiring costs affect wage setting, experimentation, and aggregate productivity. Hiring costs are reduced to increase the job finding rate by 10 percentage points. The column "Low χ_0" reports results for the case with reduced hiring costs. The column "Low χ_0, fixed U" shows results when the value of unemployment U is held constant. The column Δ shows the difference between "Low χ_0" and the baseline. The column Δ_U reports the difference between "Low χ_0, fixed U" and the baseline. The unit of Δ and Δ_U is percentage change for statistics such as entrant mass, young firm wage, risky young firm wage, and mature firm wage. For the share of experimentation, young firm share, and young firm employment share, the unit is percentage point (p.p.) change.

is not to identify the effects of any specific institution; we explicitly abstract from the heterogeneous propagation mechanisms through which particular policies operate. Instead, we seek to isolate and analyze a common channel: how institutions that influence the job-finding rate ultimately affect wage differentials between experimenting and non-experimenting firms.

Specifically, we analyze how the stationary equilibrium of the calibrated economy responds to a reduction in the scale parameter of the vacancy-cost function, χ_0 that increases the job-finding rate of unemployed workers by 10 percentage points. This policy directly raises vacancy posting by lowering the marginal cost of hiring in equation (9). The resulting increase in labor demand raises the job-finding rate, which in turn increases the value of unemployment. As discussed in Section 2.7, a higher value of unemployment lowers the wage paid by risky young firms relative to safer firms. To isolate the role of this propagation channel, which operates through the feedback from the value of unemployment to wage setting, Table 2 compares steady-state outcomes under two scenarios: one in which we evaluate the overall effects of the policy, and another one in which the value of unemployment is held fixed at its baseline level.

Table 2 reports how a reduction in hiring costs affects wages, experimentation, and the composition of firms. The overall effects of the policy are shown in Column "Low χ_0". Average wages at young firms decline by approximately 0.2%, driven entirely by a sharp drop in wages at risky young firms (–0.85%), while wages at safe young firms increase slightly (+0.2%). Wages at mature firms rise more substantially, by about 0.5%, reflecting greater productivity. The decline in relative wages at risky firms raises the share of entrants choosing to experiment by roughly 10 p.p., which in turn leads to an increase in overall firm entry. Greater experimentation raises the failure rate among young firms when they become mature and increases firm exit. As a result, fewer firms survive to maturity, raising both the share of young firms in the economy and their share of total employment.

Column "Low χ_0, fixed U" presents results from a counterfactual in which the value of unemployment is held constant at its baseline level. Although the reduction in vacancy costs leads to an increase in firm entry, the absence of a differential wage response between young firms pursuing risky and safe business models implies that the share of entrants opting for experimentation remains essentially unchanged.[10] Consequently, the effects on both the share of young firms and their employment share are also negligible.

We next examine the impact of reduced job-creation costs on aggregate productivity, focusing on the underlying transmission channels. Aggregate productivity (or TFP), defined as Y/N^{α}, where Y and N denote aggregate output and employment respectively, can be decomposed as follows:

$$TFP = \underbrace{M^{1-\alpha}}_{\text{Total mass}} \times \underbrace{\left(\frac{1}{M^{1-\alpha}} \left(\int z_k^{\frac{1}{1-\alpha}} dk \right)^{1-\alpha} \right)}_{\text{Productivity distribution}} \times \underbrace{\left(\frac{1}{\left(\int z_k^{\frac{1}{1-\alpha}} dk \right)^{1-\alpha}} \left(\frac{\int z_k^{\frac{1}{1-\alpha}} (n_k/y_k)^{\frac{\alpha}{1-\alpha}} dk}{\left(\int z_k^{\frac{1}{1-\alpha}} (n_k/y_k)^{\frac{1}{1-\alpha}} dk \right)^{\alpha}} \right) \right)}_{\text{Allocative efficiency}}, \tag{22}$$

where z_k, n_k, and y_k denote the productivity, number of workers, and output of firm k, respectively.

The first term, *total mass*, captures the idea that an increase in the number of firms—holding aggregate employment constant—lowers the scale at which each firm

[10]While the quantitative effect on experimentation is negligible, the direction remains positive: higher vacancy-filling rates benefit firms with growth potential—namely, productive young firms—thereby slightly increasing the relative attractiveness of risky experimentation.

operates. Due to decreasing returns to scale, this raises aggregate productivity. The second term, *productivity distribution*, reflects the composition of firms in equilibrium: a larger share of high-productivity firms contributes positively to aggregate productivity. The final term, *allocative efficiency*, measures the degree of labor misallocation, proxied by the dispersion in the marginal product of labor. Greater dispersion indicates poorer allocation, reducing aggregate output for a given level of employment (Hsieh and Klenow, 2009).

Table 3 presents the impact of reduced hiring costs on aggregate productivity and its decomposition. When hiring costs are lowered (Column "Low χ_0"), aggregate productivity increases by nearly 1%. The primary driver of this gain is a rise in the share of highly productive firms, driven by increased experimentation among entrants. This channel alone raises aggregate productivity by approximately 3.7%. However, this effect is partially offset by a 2.4% decline in aggregate productivity due to an increase in average firm size, as increased experimentation leads more firms to exit. Additionally, the new steady state features a larger share of experimenting firms, which exhibit more dispersed ex-post permanent productivity. The combination of this increased dispersion and labor market frictions leads to greater misallocation, reducing aggregate productivity by about 0.3%.

To assess how much the propagation channel of interest contributes to the overall increase in productivity of 1%, we recompute aggregate productivity and its decomposition while holding the value of unemployment constant (Column "Low χ_0, fixed U"). In this counterfactual, aggregate productivity still rises—by approximately 0.6%—indicating that the unemployment safety channel accounts for the remaining 0.4%. Most interestingly, the composition of gains differs markedly from the baseline scenario. The productivity improvement now comes almost entirely from an increase in the number of firms—driven by higher entry—interacting with decreasing returns to scale. Since relative wages remain unchanged in the new steady state, the share of experimenting young firms and the productivity distribution across firms are largely unaffected. As a result, the contribution of the productivity distribution to total factor productivity is minimal. Hence, the 3.7% increase in aggregate productivity, stemming from the improved productivity distribution observed under the baseline scenario, is entirely attributable to the propagation mechanism of interest.

Table 3: TFP Decomposition: Baseline vs. Lower Hiring Costs

	Baseline	Low χ_0	Δ	Low χ_0, fixed U	Δ_U
Aggregate Productivity	1.075	1.085	0.965	1.081	0.591
Total Mass	0.628	0.613	-2.383	0.632	0.588
Productivity Distribution	1.845	1.914	3.738	1.845	0.003
Allocative Efficiency	0.927	0.925	-0.297	0.927	0.000

Notes: This table shows how a reduction in hiring costs—resulting in a 10 percentage point increase in the job-finding rate—affects aggregate productivity and its decomposition. "Low χ_0" refers to the case with reduced hiring costs, and "Low χ_0, fixed U" to the same case with fixed unemployment value U. The column Δ is the difference between "Low χ_0" and the "Baseline". The column Δ_U is the difference between "Low χ_0, fixed U" and the "Baseline". The unit of Δ and Δ_U is percentage change.

A Testable Implication The model experiment above shows that an increase in the value of unemployment—driven by higher job-finding rates—raises the incentive for firms to engage in risky experimentation, ultimately leading to higher long-run productivity. These effects are driven by the differential wage responses that emerge from bargaining: workers in risky young firms, which are still subject to experimentation risk, accept lower wages compared to those in young safe firms. From this mechanism, we derive the following testable implication: among young firms, higher job-finding rates should be associated with lower wages in experimenting firms relative to non-experimenting ones.

In the next section, we test this implication using geographical variation in job finding rates across Denmark.

5 Empirical analysis

Building on the model's predictions, this section tests whether local job-finding rates shape wage-setting outcomes in line with our mechanism. Using Danish administrative data and exploiting geographical variation in job finding rates, we examine whether, among young firms, wages are lower in experimenting firms relative to non-experimenting ones when job-finding rates are higher.

5.1 Data

Our analysis uses the following administrative records from Statistics Denmark:

Employment Registry: The *Beskæftigelse for Lønmodtagere* (BFL) dataset contains monthly information for all workers residing in Denmark, including details about their employers, salaries, hours worked as well as job start and end dates, covering the period from 2008 to 2023.

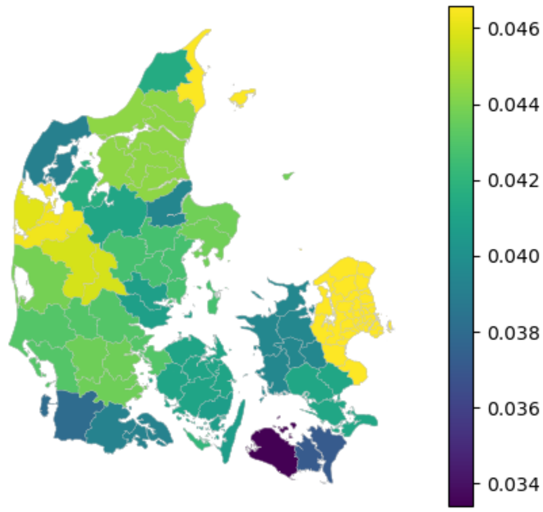
Population Registry: *Befolkningen* (BEF) is an individual-level dataset that includes information such as date of birth, gender, address, civil status, and more. We use the residential address data to map workers to their commuting zones, utilizing a mapping provided by Danmarks Statistics (DST), which identifies 29 commuting zones across the country.

Business Registry: *FIRM* contains general accounting and legal information on all businesses operating in Denmark, including, in particular, the firms' founding dates, which are required to calculate firm age.

Education Registry: *Uddannelse* (UDDA) contains information on the educational background of the Danish population. For each worker, we observe all the educational degrees they have obtained.

We construct monthly transition rates from non-employment to employment as a proxy for job finding rates. A worker is classified as non-employed if they do not appear in the BFL registry in a given month. By merging the employment and population registries, we generate a time series of job finding rates at the commuting zone level. These rates are computed as the ratio of individuals transitioning from non-employment to employment in a given period, relative to the stock of non-employed individuals in the previous month. Following Bilal (2023), we restrict the sample to male workers aged 30 to 52, as this group exhibits high and stable labor force participation, minimizing life-cycle effects. We then aggregate the monthly employment inflow rates into yearly averages for each commuting zone. Figure 2 illustrates the geographic variation in annual employment inflow rates across commuting zones. The map reveals substantial heterogeneity across areas: some commuting zones consistently exhibit markedly higher inflow rates than others. Importantly, this variation is largely persistent over time, suggesting that it reflects relatively stable differences in local economic conditions rather than transitory fluctuations. In particular, commuting zones that are structurally weaker economically tend to feature systematically

Figure 2: Job finding rate by commuting zone



lower job-finding rates.

Next, we merge the FIRM and BFL registries to create worker-level time series of wages, incorporating employer age information. The sample is restricted to private-sector employees, and to reduce noise in firm-level wage calculations, we retain only workers who remain employed at the same firm throughout the entire year. For individuals holding multiple jobs, we define the primary job as the one with the highest wage and exclude all secondary jobs. We compute the average yearly hourly wage for each worker by dividing total yearly wage income by total yearly hours worked, and we assign commuting zones based on residential information from the population registry.

To control for worker characteristics, we gather data from the employment and education registries, including age, occupation, and educational attainment, mapping degrees to years of education. Before running the regressions, we exclude observations with missing covariates. Additionally, we remove outliers, including cases with non-positive yearly wages, yearly wages exceeding 20 million DKK (i.e., about 2.7 million Euros), or non-positive or missing yearly hours worked. This leaves us with a baseline panel of approximately 16 million worker-year observations over 2008–2023. This includes approximately 2.5 million unique workers and 200,000 unique firms.

5.2 Experimenting-firms wage premia and job finding rates

5.2.1 Empirical strategy

To test the key mechanism, we construct a model-consistent measure of risky experimentation at the firm level. In the model, firms engaged in risky experimentation draw their permanent productivity from a Pareto distribution, which generates more dispersed business outcomes than those of safe entrants. Guided by this mapping between experimentation and dispersion in permanent outcomes, we classify a firm as experimenting when the *permanent* component of its sales–growth lies in the industry–cohort tail (either highly positive or highly negative); the remainder are labeled safe.

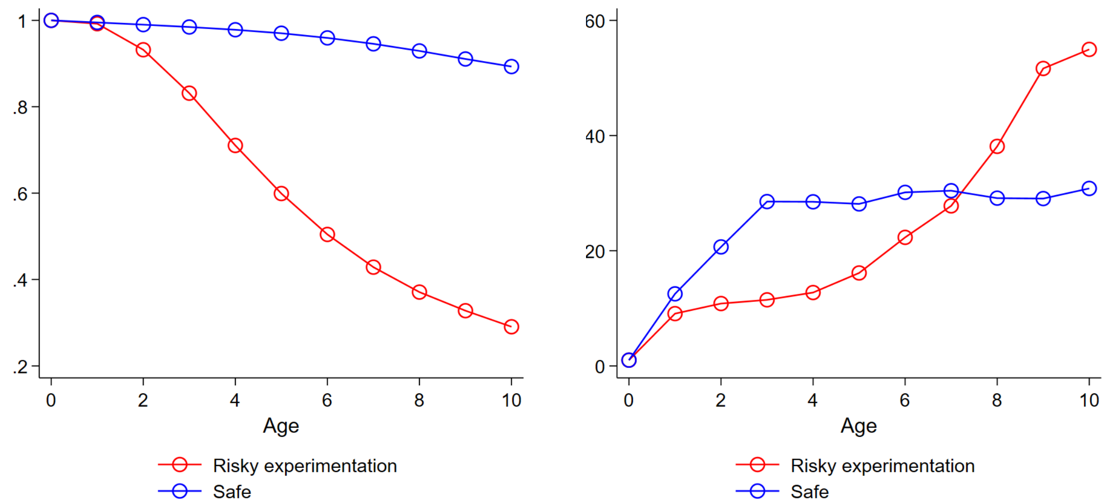
Specifically, we first define the revenue growth rate as $g_{jt} = \frac{y_{jt+1} - y_{jt}}{(y_{jt+1} + y_{jt})/2}$, where y denotes the real revenue of firm j in year t. This is the standard growth rate measure in the firm dynamics literature, originating from Davis et al. (1998) (DHS). Notably, this formulation implicitly assigns a growth rate of -2 to exiting firms, as $y_{jt+1} = 0$ by definition for firms that exit the sample. Next, we estimate the permanent component of sales growth by estimating the following regression:

$$g_{jt} = \alpha_j + \gamma_{kt} + \beta_1 \log(size_{jt}) + \beta_2 \log(age_{jt}) + \epsilon_{jt}, \tag{23}$$

where k indexes the industry to which firm j belongs. The firm fixed effects, α_j, capture permanent productivity components that are not explained by firm size, age, or industry–year conditions. Within each entry cohort and industry, we rank firms by α_j and classify those in the top $x\%$ and bottom $(50 - x)\%$ of the distribution as risky experimenters. Firms with α_j values between the top $x\%$ and bottom $(50 - x)\%$ are classified as safe. In our baseline, we set $x = 5\%$, so that the bottom 45% and top 5% are risky experimenters, while firms between the top 5% and bottom 45% are safe. This choice is guided by our calibrated model. First, in the baseline calibration, the target share of risky experimenters among entrants is 50%, and we impose the same share in the empirical classification. Second, given our calibration of entrants' initial productivity z_e and the Pareto shape parameter ξ, roughly the bottom 44% and top 6% of the permanent productivity distribution correspond to risky experimenters. Accordingly, we use $x = 5\%$ in the baseline and test robustness with $x = 1\%$ and $x = 10\%$.

To assess whether our empirical classification captures key life-cycle patterns implied by the model—and not directly targeted by the wage-regression specification in

Figure 3: The share of surviving firms (left) and relative sales (right) by age



eq. (23)—we examine survival and relative sales by firm age. Specifically, for each age a and for both experimenting and safe firms, we plot (i) the share of surviving firms and (ii) the ratio of sales at age a to sales at age 0 ($sales_a/sales_0$). Figure 3 shows that survival declines more steeply for experimenting firms, indicating a higher exit hazard, consistent with the heavier lower tail of outcomes implied by risky experimentation. In the sales panel, conditional on survival, experimenting firms eventually outgrow safe firms and attain higher relative sales, consistent with selection on a heavier upper tail.

Building on the firms' classification derived from eq.(23), we now test whether the wage differential between experimenting and non-experimenting firms decreases as unemployment becomes less costly, proxied by higher job-finding rates. In our theoretical model, only young firms—those that have not yet drawn their permanent productivity—engage in risky experimentation. In contrast, mature firms, regardless of whether they began as safe or risky, have resolved this uncertainty and no longer take major risks, though they continue to face standard idiosyncratic shocks. Reflecting this distinction, we restrict the sample to young firms (under three years old) and estimate variants of the following baseline regression:

$$\ln w_{it} = \eta_t + \beta X_{it} + \gamma_1 \hat{\chi}_{J(i,t)} + \gamma_2 f_{M(i,t)} + \delta(\hat{\chi}_{J(i,t)} \times f_{M(i,t)}) + \epsilon_{it}, \qquad (24)$$

where w_{it} denotes the real hourly wage of worker i in year t, who is employed at firm $j = J(i,t)$ and resides in local labor market (commuting zone) $m = M(i,t)$. We include year fixed effects, η_t, and X_{it} collects the full set of additional controls and fixed effects included in a given specification, which we enrich progressively across columns of Table 4. These controls include log-transformed years of education, and log-transformed age normalized by 40 (along with its square and cube). Following Babina et al. (2019), we flexibly control for age and education by including a cubic in (log) age and its interactions with (log) education; when worker fixed effects are included, the linear age and education terms are omitted due to collinearity.

We define $f_{M(i,t)}$ as the job-finding rate from nonemployment in worker i's commuting zone $M(i,t)$, and $\hat{\chi}_{J(i,t)} \in \{0,1\}$ as the estimated experimentation indicator for the employing firm $J(i,t)$, constructed from eq. (23); $\hat{\chi}_{J(i,t)} = 1$ identifies firms classified as experimenting. The job-finding rate $f_{M(i,t)}$ is standardized—demeaned and divided by its standard deviation—to facilitate interpretation of the regression coefficients. Our main coefficient of interest is δ, which we expect to be negative.

5.2.2 Results

Table 4 shows that the coefficient on Experimentation, γ_1, is positive but statistically insignificant across all specifications. While the sign is consistent with the calibrated model's prediction in Table 2, the lack of precision likely reflects that the average wage differential between experimenting and non-experimenting young firms (conditional on the controls and fixed effects in the specification) is not pinned down by a single force in the data. One plausible offsetting channel is the financing and compensation structure emphasized by Michelacci and Quadrini (2005): financially constrained young firms may effectively "borrow from employees" by offering lower initial pay in exchange for steeper subsequent wage growth or other upside conditional on survival and success, which would work to depress current wages at experimenting firms. Our baseline model abstracts from this borrowing/contracting margin, but it may be present in practice and could attenuate the average wage difference, helping explain why γ_1 is positive yet imprecisely estimated.

Before turning to the interaction, note that the main effect of the job–finding rate is positive and statistically significant in all columns. Given the inclusion of the interaction, this coefficient pertains to non-experimenting firms ($\chi = 0$): a one–standard–deviation increase in job finding raises their wages by about 0.23–0.42 percent across specifications (0.23 p.p. in our preferred firm–FE model, col. 5). We now turn to the interaction term, the key object of interest, which captures how this

Table 4: Experimentation and job finding rate

Experimentation	0.00507	0.00466	0.00393	0.00412	0
	(0.00367)	(0.00367)	(0.00368)	(0.00364)	(.)
Job Finding Rate	0.00422***	0.00317**	0.00315**	0.00421***	0.00231*
	(0.00154)	(0.00153)	(0.00152)	(0.00153)	(0.00128)
Exp. × Job Finding Rate	-0.00532***	-0.00477***	-0.00486***	-0.00558***	-0.00394**
	(0.00178)	(0.00178)	(0.00178)	(0.00171)	(0.00168)
Observations	399,053	399,053	399,053	399,038	389,738
R-squared	0.900	0.900	0.901	0.901	0.940
Time-Varying Worker Controls	No	Yes	Yes	Yes	Yes
Worker FE	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	No	No
Firm FE	No	No	No	No	Yes
Year FE	Yes	Yes	Yes	No	Yes
Year x Industry FE	No	No	No	Yes	No

Notes: This table presents the baseline results for the wage premium at experimenting young firms and its interaction with labor market conditions. The sample consists of a matched worker-year panel from 2008 to 2023, with the dependent variable being the log of yearly real hourly wages. Time-varying worker controls include worker age squared, worker age cubed, worker age interacted with education, worker age squared interacted with education and worker age cubed interacted with education. Worker age is log-transformed and normalized by 40, while education is measured in years of study and also log-transformed. In regressions with worker fixed effects, worker age and education are excluded as linear controls since they are collinear with the fixed effects. The job finding rate is calculated as the ratio of all inflows into employment divided by stock of non-employed. Note that the job finding rate is demeaned and divided by the standard deviation, so a unit increase in this rate is interpreted as a change of 1 standard deviation. Standard errors are clustered at the level of firm and worker and reported in parenthesis. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

wage response differs between experimenting and non-experimenting firms.

Table 4 presents our main empirical test of whether the wage gap between experimenting and non-experimenting young firms systematically varies with local labor market conditions. Across all specifications, the interaction between the firm-level experimentation measure and the job finding rate is consistently negative and statistically significant. However, the identifying variation differs across columns. In columns 1–4, which omit firm fixed effects, the interaction term is identified from both within-firm and across-firm variation: we compare wages of workers residing in commuting zones with different job-finding rates both within a given firm's workforce and across firms that differ in experimentation status and in the job-finding conditions faced by their employees. Interpreted through the across-firm variation, $\delta < 0$ means that commuting zones with higher job-finding rates exhibit a smaller experimenting–safe wage differential—experimenting firms pay relatively less in high–job-finding areas.

Absent industry controls, a negative δ could partly reflect industry composition: commuting zones with higher job-finding rates may be disproportionately specialized in industries with lower wage premia. Column 3 therefore adds industry fixed effects, so identification comes from within-industry variation across locations. This allows us to assess whether, holding the industry constant, experimenting firms still pay relatively less in high job-finding commuting zones.

Even within industries, a negative δ could reflect industry-year booms and busts rather than our mechanism. For example, in expansionary years, local job-finding rates rise, and if product demand (or revenues) expands more for safe firms than for experimenting firms, wages at safe firms may increase more, mechanically compressing the experimenting–safe wage differential. Column 4 therefore absorbs industry-by-year fixed effects, so identification comes from within-industry, within-year cross-sectional variation across commuting zones, net of common industry-year demand shocks.

Finally, our preferred specification in column 5 includes firm fixed effects, thus exploiting within-firm, across-worker variation in exposure to local labor market conditions. In this case, identification is sharpened by workers at the same firm facing different outside options depending on the commuting zone they reside in. This is a particularly demanding specification, as it absorbs all time-invariant firm characteristics—including compensation policies, management style, and unobserved firm quality—leaving identification to rely solely on within-firm, across-worker variation in exposure to local labor markets. Yet, despite this stringent control structure, the interaction coefficient remains statistically significant at the 5 percent level and maintains a magnitude in the same broad range as previous specifications. This provides robust evidence that experimentation-related wage premia fall in tighter labor markets, even when all firm-specific confounders are accounted for.

The magnitude of the interaction term is economically meaningful. In column 5, a one standard deviation increase in the job finding rate reduces the wage differential between experimental and non-experimental firms by approximately 0.4 p.p. This pattern is consistent with the mechanism in the theoretical model: when labor market conditions improve and unemployment becomes less risky, workers are more willing to accept relatively lower wages in firms pursuing uncertain but potentially high-return ventures.

Alternative mechanism: financing constraints and credit-market conditions. One potential alternative interpretation of the interaction term in Eq. (24) is that it captures variation in credit-market conditions rather than labor-market risk. In particular, if experimenting young firms rely more on external finance, then they should be disproportionately exposed to credit tightening in downturns or in depressed local labor markets (e.g., tighter bank lending or binding covenants), as emphasized by the broader literature on financial frictions and firm activity (Gertler and Gilchrist, 1994; Chodorow-Reich, 2014; Chava and Roberts, 2008), and by work linking financing conditions to the composition of startup innovation across cycles (Nanda and Rhodes-Kropf, 2013; Kerr and Nanda, 2015). Under this mechanism, when liquidity dries up, experimenting firms would be relatively more constrained and hence less able to pay, implying that the experimenting–safe wage differential should *compress* precisely when job finding is low (in recessions or in low-f regions). Equivalently, in Eq. (24) one would expect a *positive* interaction: higher job-finding rates (looser credit conditions) should be associated with a *larger* experimenting premium, whereas lower job finding (tighter credit) should reduce it. This prediction is the opposite of what we estimate: in Table 4 the interaction coefficient is robustly negative, implying that the experimenting–safe wage differential is *smaller* in high job-finding markets and, if anything, *larger* when job finding is low. Thus, while financing frictions may help rationalize why the average premium γ_1 is muted (consistent with "borrowing from employees" as in Michelacci and Quadrini, 2005), a financing-dryout story cannot account for the negative interaction that is central to our mechanism; if anything, it would bias the interaction toward the opposite sign.

5.3 Young-firm wage premia and job-finding rates

The experimentation exercise above provides a direct test of the mechanism—linking wage setting to experimentation exposure, but it relies on an empirically constructed measure of experimentation and is therefore exposed to measurement error. As a complementary indirect check that avoids any classification, we examine how the young–mature wage differential varies with local job-finding rates. This test is indirect because firm age is only an imperfect proxy for experimentation exposure, even in the model: experimentation is an entry-stage choice, so only a subset of young firms experiment, while mature firms have already resolved entry-stage uncertainty and no longer face experimentation-related risk. At the same time, the premise that innovative activity tied to the creation of new product lines is disproportionately concentrated early in the firm life cycle is supported empirically by Akcigit and Kerr (2018). Hence, while coarse, the young–mature comparison provides a model-consistent and empirically motivated way to probe the same prediction using an observed dimension that is systematically related, though not perfectly aligned, with experimentation exposure.

The model delivers a clear prediction for this aggregate comparison. In Table 2, raising the job-finding rate (via lower hiring costs) reduces wages at risky young firms while raising wages at mature firms, implying that the young–mature wage differential should decline as job-finding improves. Moreover, a pure financing-constraints interpretation would generally predict the opposite pattern: if young firms are more exposed to credit tightening, then in low job-finding markets (where funding conditions tend to be worse) young-firm wages should fall *relative* to mature-firm wages, compressing the young–mature differential and inducing a *positive* correlation between job finding and the differential (e.g., Gertler and Gilchrist, 1994; Chodorow-Reich, 2014; Nanda and Rhodes-Kropf, 2013).

To test this hypothesis, we estimate variants of the following regression:

$$\ln w_{it} = \eta_t + \beta X_{it} + \gamma_1 Y_{J(i,t)} + \gamma_2 f_{M(i,t)} + \delta \left(Y_{J(i,t)} \times f_{M(i,t)} \right) + \epsilon_{it}, \qquad (25)$$

where $Y_{J(i,t)}$ denotes an indicator function that equals 1 if a firm is classified as young (i.e., less than three years old). Consistent with the model's prediction, Table 9 in Appendix shows a negative and statistically significant interaction between the *Young* indicator and the local job-finding rate across specifications with worker fixed effects, rich time-varying worker controls, industry and industry×year fixed effects, and, crucially, firm fixed effects. In the most demanding designs, identification comes from *within-firm* comparisons of workers who face different outside options because they reside in different commuting zones. For an in-depth analysis on young-mature firm differentials and how they relate to job finding rates we refer to the Appendix Section B.2. While these estimates are observational and should be interpreted as conditional correlations, their sign and robustness line up closely with the model and with the experimenting-versus-safe-firms evidence above. We view the alignment of the indirect and direct approaches as reinforcing the interpretation of our main findings and as motivation for the survey experiment that follows, which is designed to isolate the worker-side career-value channel cleanly.

5.4 From microdata to survey evidence

The estimates in Eq. (24) are valuable because they use *realized wage outcomes* for a large population of workers, providing externally valid evidence from actual labor markets. Yet these estimates have two important limitations. First, identification is observational: conditioning on rich sets of worker, firm, industry, and time controls mitigates endogeneity concerns, bringing the analysis closer to—but still short of—causal identification, since variation in $f_{M(i,t)}$ is not randomized. Second, eq. (24) is an equilibrium regression: both wages and local job-finding rates are jointly determined in general equilibrium, reflecting the interaction of workers' outside options, firms' hiring behavior, and wage bargaining. The estimated coefficients therefore capture the equilibrium comovement of wages and job-finding rates—consistent with the model's mechanism—but not a partial-equilibrium causal effect of job-finding on wages.

Link to the theory. Section 2.7 develops intuition through a partial-equilibrium thought experiment that varies the value of unemployment U in the bargaining problem while holding the firm's pre-wage surplus P fixed. This isolates how the feedback from U through the worker's career value C_χ affects negotiated wages differently across experimentation types ($\chi \in \{\text{risky}, \text{safe}\}$). In an ideal empirical setting, one would exploit variation in workers' perceived U across firms with different experimentation intensity. Because U is unobserved, we approximate it with the local job-finding rate f, a primary determinant of U. In practice, however, changes in f also influence firms' hiring conditions and thus the pre-wage surplus P, because job-finding rates and vacancy-filling rates are tightly linked through equilibrium labor-market tightness; observed wage responses therefore reflect not only the worker-side career-value channel emphasized by the model but also the accompanying firm-demand effects that arise in general equilibrium.

How large is the firm-demand channel in the model? Our counterfactual experiment in Table 2 shows that this channel is quantitatively minor. When we shock hiring costs but *hold U fixed*, there is virtually no change in the wage differential between experimenting and non-experimenting young firms even though tightness feeds back into the vacancy-posting condition and thus into P. In other words, allowing P to adjust without letting U move does not generate an appreciable experimenting–safe wage tilt. This indicates that the *career-value channel*—the part mediated by U

through C^{χ}—is the dominant driver of the model-implied interaction.

Implication for measurement in the registers. In the data, the firm-demand channel need not be negligible and may contaminate the precise estimate of the career-value slope of interest. Hence $\widehat{\delta}$ from Eq. (24) should be interpreted as a reduced-form interaction that combines (i) the causal worker-side mechanism emphasized by the theory and (ii) equilibrium firm-demand co-movements induced by local labor-market conditions, as well as any other residual unobserved local shock that jointly affect job-finding rates and wage differentials despite the controls and fixed effects.

Designing a clean test. To isolate the mechanism, the next section implements a *supply-side analogue* of Eq. (24). In this analogue, the dependent variable is not the realized equilibrium wage but the worker's *stated acceptance threshold* for a hypothetical offer. Conceptually, this threshold is the same object that AOB delivers in equilibrium—the lowest wage consistent with acceptance—but here it is elicited in a partial-equilibrium vignette: respondents state the wage differential required to switch from a safe to a risky firm, holding job attributes fixed and randomizing only perceived unemployment duration. By design, this abstracts from equilibrium adjustments in labor-market tightness and firm surplus. In this setting, the analogue of δ identifies the causal career-value slope, with the firm-demand channel set to zero by construction.

6 A randomized survey experiment

6.1 Survey description

Sampling and implementation. We embedded a short research module as an addendum to Danmarks Nationalbank's *Survey of Consumers' Expectations* (*Nationalbankens forventningsundersøgelse*), a survey designed to be representative of the Danish population.[11] The survey is fielded monthly and sent to 6,000 Danish residents, comprising roughly 5,000 newly sampled individuals and about 1,000 recontacts who responded in the same month of the previous year; in a typical month, about 1,000 of the 6,000 invited individuals complete the survey. Statistics Denmark administered the instrument as part of the standard fielding. The module was triggered

[11]The survey module is registered in the repository (Faccini, Renato and Seho Kim, 2026).

only for respondents who, in the labor–market block, reported being employed and subsequently indicated holding a *permanent* contract; only those respondents were routed to the special module. Our sampling restrictions imply roughly 600 eligible respondents per month.

Survey design and content. To minimise researcher-demand bias, the module elicits only *one* compensating–differential choice per respondent. The structure follows a simple progression: respondents (i) state their expected job-finding duration if unemployed, (ii) read a vignette contrasting a stable firm and an experimental young firm, and (iii) indicate the pay change that would make them switch. Each respondent answers a single vignette question; no follow-up or re-elicitation is made.

The first question establishes the respondent's perceived job-finding prospects:

> **Q1. Expected unemployment duration.**
> *Imagine you lost your job today. How long do you think it would take you to find another job? Please provide your best guess.*
> *Number of months:* ______________

The second and third questions introduce the hypothetical job-choice scenario. Respondents are asked to imagine that their job-finding time could be either *twice* or *half* the duration they previously stated, with the assignment randomised across individuals. They then compare two otherwise identical firms that differ only in their risk and growth potential:[12] [13]

> **Vignette.**
> Imagine that if you were to lose your job in the future, it would take you **twice/half as long** to find a new one as you wrote earlier
>
> Now suppose you work at **Company A**. Company A makes an existing, well-known product already sold on the market. Out of 100 firms of this

[12] The failure-risk probabilities used in the vignette (4% and 20%) are chosen to be empirically plausible, based on calculations from the Danish register microdata.

[13] The vignette is phrased as an employed worker receiving an outside offer. While our model abstracts from explicit EE flows, our mechanism hinges on alternating–offer bargaining making wages load on the worker's *career value*, whose response to job-finding conditions is separation-risk dependent. Since this career-value term enters AOB regardless of whether the worker is hired from unemployment or from another job, the implied sensitivity of the risky–safe wage differential to job finding does not hinge on the worker being hired from unemployment. See the end of Section 2.7.

type, about **4** close each year. It is stable and not expected to change much or grow fast. Think of yourself doing the same job you do now, just at Company A.

You then receive an offer from **Company B**. Company B is developing a new, untested product that is not yet on the market. Out of 100 firms of this type, about **20** close each year. If the product succeeds, the company may grow; if it fails, it may close.

When you compare the two companies, assume the working conditions are the same—same commute, working hours, coworkers, duties, and work environment. **The only differences are the chances the company could close over the next year and its potential growth.**

Respondents then indicate how their job-choice depends on pay:

Q2a. Switching condition.
*Suppose Company B offers you the job. Remember, that should you lose your job in the future, it would take you **twice/half as long** to find a new one. How would your decision depend on pay?*

☐ I would only switch if the pay were higher than at Company A.

☐ I would also switch if the pay were the same as at Company A.

☐ I would even switch if the pay were lower than at Company A.

Conditional on the chosen response, the following quantitative entry captures the reservation premium or discount:

Q2b. Reservation premium/discount.
If you would only switch for higher pay: By about how much higher would the pay at Company B need to be for you to accept the job? *Pay increase:* ______________%.
If you would also switch for lower pay: By about how much lower could the pay at Company B be, and you would still take the job? *Pay decrease:* ______________%.

The vignette deliberately avoids assigning a numeric growth upside to Company B relative to Company A. Instead, it conveys qualitatively that success may bring growth while failure may lead to closure. This design choice reduces cognitive burden but leaves the level of the stated wage differential unanchored. This is not a concern for our purposes because our object of interest is not the level of the premium per se (the analogue of γ_1 in Eq. (24)), but how it responds to unemployment conditions (the analogue of δ). Since the growth narrative is held fixed across respondents and only expected unemployment duration is randomized, any level effects do not affect our estimand: we identify how the risky–safe reservation differential *changes* with unemployment duration, rather than its absolute magnitude.

6.2 Regression specification and result

We denote the expected unemployment duration of respondent i, D_i, elicited in Q1. The vignette randomly assigns a shock $\Delta \ln D_i \in \{-\ln 2, +\ln 2\}$: $+\ln 2$ for respondents assigned a doubling of unemployment duration, and $-\ln 2$ for those assigned a halving. Second, we denote the compensating wage differential between risky and safe young firms z_i, elicited in Q2b. This differential is measured in percentage terms, $z_i \equiv 100 \times (\log w_{i1} - \log w_{i0})$, where w_{i1} and w_{i0} are the required wages when respondent i joins a risky and a safe young firm, respectively. We observe only the compensating differential z_i, not the individual wage levels. Lastly, we control for age, gender, number of children, mortgage status, household leverage, municipality and education fixed effects.

Next, to address selection into survey response, we compute survey weights for each respondent using iterative proportional fitting ("raking"), based on age, gender, education, number of children, mortgage status, and household leverage. The raking targets are drawn from the population of working individuals in Denmark as of June 2025, the most recent demographic information available.

Based on this, we estimate the following equation and report the estimated coefficient and its p-value:

$$z_i = \underset{p=0.003}{\overset{\text{coef.}=5.13}{\hat{b}_D}} \Delta \ln D_i + \boldsymbol{X}_i + \varepsilon_i, \tag{26}$$

where $\boldsymbol{X}_i$ is a vector of control variables. The estimated coefficient $\hat{b}_D = 5.13$ implies that a doubling unemployment duration (i.e., lower unemployment safety) is associated with a 3.6-percentage-point ($= 5.13 \times \log 2$) increase in the compensating wage differential. This effect is statistically significant at the 1% level, with a p-value of

0.003.

7 Conclusion

This paper proposes a mechanism linking the cost of unemployment to aggregate productivity through the risky experimentation of new entrants. We develop a heterogeneous firm-dynamics model with a frictional labor market and alternating–offer bargaining, and show that higher job-finding rates increase the share of entrants that experiment and, in turn, raise productivity. Using cross-regional variation in Danish job-finding rates, we find that wage differentials—both between experimenting and non-experimenting firms and between young and mature firms—decline where job-finding rates are higher, consistent with the model's unemployment channel. A randomized module embedded in Danmarks Nationalbank's Survey of Consumers' Expectations provides direct causal support: exogenously increasing expected unemployment duration raises the wage differential required to accept employment at riskier firms. Taken together, the register and survey evidence supports the view that a lower cost of unemployment encourages risky experimentation and enhances long-run productivity.

Our findings suggest that institutional environments that support job creation and reemployment prospects can raise productivity by reducing the wage costs associated with experimentation at young firms. At the same time, we do not model specific institutions or identify the effects of particular policies; our quantitative exercise treats job-finding conditions as a reduced-form shifter. Determining which policy levers—e.g., unemployment insurance design, activation and placement services, training, or hiring regulations—most effectively improve job-finding prospects and thereby foster experimentation is an important avenue for future research. This question is especially salient in the current AI-driven transformation, where new technologies are opening scope for new entrants and business models, and where labor-market institutions may shape how readily transformative firms emerge and scale.

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APPENDIX TO

Safety in Unemployment and Risky Experimentation of Young Firms

by Renato Faccini, Seho Kim, and Javier Miranda

A Appendix for model

A.1 Evolution of the distribution of firms

We denote the distribution of safe, risky young firms, and risky mature firms before posting vacancies as $\Gamma_s(\boldsymbol{z}, n_{-1})$, $\Gamma_{ry}(\boldsymbol{z}, n_{-1})$, and $\Gamma_{rm}(\boldsymbol{z}, n_{-1})$, respectively. The distribution of safe firms, Γ_s, evolves as follows:

$$\Gamma'_s((z_e, z'_i), n) = \int\int_{n=(1-\zeta)n^{s,*}((z_e,z_i),n_{-1})} (1-\eta)(1-p^s_x((z_e, z'_i), n))d\Pi(z'_i|z_i)d\Gamma_s((z_e, z_i), n_{-1}) + (1-P(R))M_e \mathbb{1}_{n=1}\mathbb{1}_{z'_i=\mu_{z_i}}). \tag{27}$$

The first term captures the mass of surviving safe firms. Firms experience worker separations at rate ζ, update their temporary productivity according to $d\Pi(z'_i|z_i)$, and survive both exogenous and endogenous exit with probabilities $1-\eta$ and $1-p^s_x$, respectively. The second term reflects inflows from new entrants, M_e, choosing the safe route with probability $1-P(R)$, each starting with one worker and an average productivity draw.

Similarly, the distribution of risky mature firms, Γ_{rm}, evolves as:

$$\Gamma'_{rm}((z_m, z'_i), n) = \int\int_{n=(1-\zeta)n^{rm,*}((z_m,z_i),n_{-1})} (1-\eta)(1-p^{rm}_x((z_m, z'_i), n))d\Pi(z'_i|z_i)d\Gamma_{rm}((z_m, z_i), n_{-1}) + \int\int_{n=(1-\zeta)n^{rs,*}((z_e,z_i),n_{-1})} \varphi(1-\eta)(1-p^{rm}_x((z_m, z'_i), n))d\Pi_R(z_m)d\Pi(z'_i|z_i)d\Gamma_{rs}((z_e, z_i), \tag{28}$$

Unlike safe firms, risky mature firms do not receive inflows from new entrants. Instead, their only source of inflows comes from risky young firms that successfully transition into maturity after drawing a permanent productivity realization, z_m with probability φ.

Lastly, the distribution of risky young firms, Γ_{rs}, evolves as:

$$\Gamma'_{ry}((z_e, z'_i), n) = \int\int_{n=(1-\zeta)n^{ry,*}((z_e,z_i),n_{-1})} (1-\varphi)(1-\eta)(1-p_x^{ry}((z_e, z'_i), n))d\Pi(z'_i|z_i)d\Gamma_{ry}((z_e, z_i), n_{-1}) + P(R)M_e \mathbb{1}_{n=1}\mathbb{1}_{z'_i=\mu_{z_i}}. \tag{29}$$

A.2 Labor market clearing

We assume that the total mass of potential workers is 1, which gives the following condition:

$$u + \int n^{s,*}(\boldsymbol{z}, n_{-1})\, d\Gamma_s(\boldsymbol{z}, n_{-1}) + \int n^{ry,*}(\boldsymbol{z}, n_{-1})\, d\Gamma_{ry}(\boldsymbol{z}, n_{-1}) + \int n^{rm,*}(\boldsymbol{z}, n_{-1})\, d\Gamma_{rm}(\boldsymbol{z}, n_{-1}) = 1, \tag{30}$$

where u represents the mass of unemployed workers after search and matching take place, and $\Gamma_s(\boldsymbol{z}, n_{-1})$, $\Gamma_{ry}(\boldsymbol{z}, n_{-1})$, and $\Gamma_{rm}(z, n_{-1})$ denote the steady-state distributions of safe firms, risky young firms, and risky mature firms, respectively.

In addition, labor market tightness is computed as:

$$\theta = \frac{\int v^{s,*}(\boldsymbol{z}, n_{-1})\, d\Gamma_s(\boldsymbol{z}, n_{-1}) + \int v^{ry,*}(\boldsymbol{z}, n_{-1})\, d\Gamma_{ry}(\boldsymbol{z}, n_{-1}) + \int v^{rm,*}(\boldsymbol{z}, n_{-1})\, d\Gamma_{rm}(\boldsymbol{z}, n_{-1})}{u_0}, \tag{31}$$

where $v^{s,*}(\boldsymbol{z}, n_{-1})$, $v^{ry,*}(\boldsymbol{z}, n_{-1})$, and $v^{rm,*}(\boldsymbol{z}, n_{-1})$ represent the optimal vacancy postings for safe firms, risky young firms, and risky mature firms, respectively. Here, u_0 represents the mass of unemployed workers before search and matching take place, and thus enters the definition of market tightness.

A.3 Nash and alternating offer bargaining

First, we examine how changes in job-finding rates affect the value of unemployment and, in turn, how these changes translate into adjustments in the flow wage within a simple search-and-matching framework under Nash bargaining and alternating-offer bargaining. We show that, under Nash bargaining, the flow wage does not depend on the match separation rate, whereas this independence fails to hold under alternating-offer bargaining.

Second, we investigate whether this first result—that the flow wage is independent of the match separation rate under Nash bargaining—can be overturned when workers have concave utility. We show that even with concave utility, the flow wage remains independent of the match separation rate.

For analytical tractability, we employ the standard Diamond–Mortensen–Pissarides model and focus on its steady-state properties.

Proposition 1 *Consider a simplified Diamond–Mortensen–Pissarides search-and-matching framework in which a firm corresponds to a single job matched with one worker. Under Nash bargaining, the equilibrium flow wage is independent of the firm-level match separation rate s. Consequently, changes in the job-finding rate affect the flow wage independently of the match separation rate, i.e.,*

$$\frac{\partial^2 w^{Nash}}{\partial s\, \partial f} = 0.$$

In contrast, under alternating-offer bargaining, the equilibrium flow wage depends on the firm-level match separation rate. In particular, the interaction between the job-finding rate and the match separation rate is strictly negative,

$$\frac{\partial^2 w^{AOB}}{\partial s\, \partial f} < 0.$$

Proof. Before comparing Nash and alternating-offer bargaining, we first define the relevant objects. The present discounted value of production, P, is given by

$$P = y + \beta\big[s \cdot 0 + (1-s)P'\big] \Longrightarrow P = \frac{y}{1-\beta(1-s)}, \tag{32}$$

where y is the per-period output, s is the match separation rate, and β is the discount factor. The second equality follows from the steady-state condition $P = P'$.

Similarly, we define the present discounted value of wages, W, as in (14),

$$W = w + \beta\big[s \cdot 0 + (1-s)W'\big] \Longrightarrow W = \frac{w}{1-\beta(1-s)}, \tag{33}$$

and the career value, C, as in (15),

$$C = 0 + \beta\big[sU' + (1-s)C'\big] \Longrightarrow C = \frac{\beta s}{1-\beta(1-s)}U.$$

The net outside option, $U - C$, is computed as follows:

$$U - C = U - \frac{\beta s}{1-\beta(1-s)}U = \frac{1-\beta}{1-\beta(1-s)}U. \tag{34}$$

Nash bargaining

Under Nash bargaining, the wage is determined by splitting the total match surplus in fixed proportions according to the bargaining power of the firm and the worker. The total surplus, S, is

$$S = (P - W) + (W + C - U) = P + C - U,$$

and the wage is determined such that the firm surplus, $P - W$, is a fixed proportion of the total surplus, i.e.,

$$(P - W) = (1 - \gamma)(P + C - U),$$

where γ denotes the worker's bargaining power.

Thus, the present discounted value of wages is given by

$$W = \gamma P + (1 - \gamma)(U - C).$$

By plugging in (32), (33), and (34), the wage equation can be written as

$$\frac{w}{1 - \beta(1 - s)} = \gamma \frac{y}{1 - \beta(1 - s)} + (1 - \gamma) \frac{1 - \beta}{1 - \beta(1 - s)} U.$$

Multiplying both sides by $1 - \beta(1 - s)$ yields the flow wage under Nash bargaining, w^{Nash},

$$w^{\text{Nash}} = \gamma y + (1 - \gamma)(1 - \beta)U.$$

Thus, $\frac{\partial^2 w^{\text{Nash}}}{\partial s \partial f} = 0$. This shows that, under Nash bargaining, the flow wage does not depend on the match separation rate. Consequently, when the job-finding rate changes and thereby affects the value of unemployment, U, equilibrium flow wages adjust independently of the firm-level match separation rate.

Alternating offer bargaining (AOB)

For notational simplicity and to facilitate comparison with Nash bargaining, I assume that the flow return to workers, z_b, in (18) and the flow cost to firms, γ_b, in (19) are both zero.

Then, similar to the conditions in (18) and (19), in a subgame-perfect equilibrium under alternating-offer bargaining, both workers and firms must be indifferent between accepting and rejecting the other party's offer. For workers,

$$\begin{aligned} W + C &= W + (C - U) + U \\ &= \delta_b U + (1 - \delta_b)\beta_b\big(W_k + (C - U) + U\big), \end{aligned}$$

and for firms,

$$P - W_k = (1-\delta)\beta(P - W),$$

where δ_b is the probability of bargaining breakdown when one party rejects the other's offer, β_b is the discount factor during bargaining, and W and W_k denote the present discounted values of wages offered by firms and workers, respectively.

Solving for W yields

$$W = \frac{\beta_b(1-\delta_b)}{1+\beta_b(1-\delta_b)}P + \frac{1}{1+\beta_b(1-\delta_b)}(U - C) \\ - \frac{(1-\beta_b)(1-\delta_b)}{1-\beta_b^2(1-\delta_b)^2}U.$$

By plugging in (32), (33), and (34), and multiplying both sides by $1-\beta(1-s)$, we obtain the following flow wage under alternating-offer bargaining:

$$w^{\text{AOB}} = \eta y + (1-\eta)(1-\beta)U \\ - \frac{(1-\beta)(1-\delta)}{1-\beta^2(1-\delta)^2}(1-\beta(1-s))U,$$

where $\eta \equiv \frac{\beta(1-\delta)}{1+\beta(1-\delta)}$.

Thus, the flow wage under alternating-offer bargaining, w^{AOB}, depends on the match separation rate, s. More importantly, $\frac{\partial^2 w^{\text{AOB}}}{\partial s \partial f} < 0$ as $\frac{\partial U}{\partial f} > 0$, implying that an increase in the job-finding rate leads to a relatively larger decline in flow wages for firms with higher match separation rates. ■

Proposition 2 *Consider a simplified Diamond–Mortensen–Pissarides search-and-matching framework in which a firm corresponds to a single job matched with one worker. Assume that the worker's preferences are represented by a concave utility function, $u(\cdot)$. Under Nash bargaining, the equilibrium flow wage is independent of the firm-level match separation rate s. Consequently, changes in the job-finding rate affect the flow wage independently of the match separation rate, i.e.,*

$$\frac{\partial^2 w^{Nash,u}}{\partial s\, \partial f} = 0.$$

Proof. Since firms are risk neutral, they share the same present discounted value representation for productivity and wages as in Proposition 1. To distinguish between the present discounted value of wages for firms and that for workers, we denote the former by W^f and the latter by W^e.

By (32) and (33),

$$P = \frac{y}{1-\beta(1-s)}, \tag{35}$$

and

$$W^f = \frac{w}{1-\beta(1-s)}. \tag{36}$$

The present discounted value of wages for the worker, W^e, is given by

$$W^e = u(w) + \beta\big[s \cdot 0 + (1-s)W^{e'}\big] \Longrightarrow W^e = \frac{u(w)}{1-\beta(1-s)}. \tag{37}$$

The net outside option value, $U - C$, remains the same as in (34),

$$U - C = \frac{1-\beta}{1-\beta(1-s)}U, \tag{38}$$

where U includes the utility of unemployment benefits $u(b)$; however, this does not affect the representation of $U - C$ itself.

In this case, the Nash bargaining outcome is derived as follows:

$$w^{Nash,u} = \arg\max_w (P - W^f)^{1-\gamma}(W^e + C - U)^{\gamma},$$

and the first-order condition satisfies

$$\gamma(P - W^f) = (1-\gamma)(W^e + C - U) \times \frac{1}{u'(w)}.$$

Substituting (35), (36), (37), and (38), the flow wage $w^{Nash,u}$ satisfies

$$\gamma\big(y - w^{Nash,u}\big) = (1-\gamma)\big(u(w^{Nash,u}) - (1-\beta)U\big) \times \frac{1}{u'(w^{Nash,u})}.$$

Thus, again, $w^{Nash,u}$ is independent of the match separation rate, and $\frac{\partial^2 w^{\text{Nash,u}}}{\partial s\, \partial f} = 0$ holds.

■

A.4 Computational algorithm

1. Guess tightness θ, the wage schedules $w^j(\boldsymbol{z}, n)$, and the value of an additional worker $J^j(\boldsymbol{z}, n)$, $j \in \{s, rs, rm\}$. Initialize the mass of entrants $M_e = 1$.

2. By using (9), compute the optimal hiring function $n^j(\boldsymbol{z}, n_{-1})$.

3. Update $J^j(\boldsymbol{z}, n)$, $i \in \{s, rs, rm\}$ using (7) and (8) iterate 2-3 until $J^j(\boldsymbol{z}, n)$ converges. Now, we have $V^j(\boldsymbol{z}, n_{-1})$ and $V_c^j(\boldsymbol{z}, n_{-1})$, $j \in \{s, rs, rm\}$.

4. Using (5) and (6), compute the value of entrants and the probability of risky

experimentation.

5. Check the free entry condition $\mathcal{E} = \psi_e$. If $\mathcal{E} > \psi_e$, increase θ, and decrease θ otherwise. Iterate 2-5 until $J^j(\boldsymbol{z}, n)$ converges and the free entry condition holds. Use a bi-section method to implement this.

6. According to the policy function $n^j(\boldsymbol{z}, n_{-1})$, exit rules, and the exogenous productivity process, compute the steady state distribution of firms, $\Gamma_s(\boldsymbol{z}, n)$, $\Gamma_{rs}(\boldsymbol{z}, n)$ and $\Gamma_{rm}(\boldsymbol{z}, n)$.

7. Using $\Gamma_s(\boldsymbol{z}, n)$, $\Gamma_{rs}(\boldsymbol{z}, n)$, $\Gamma_{rm}(\boldsymbol{z}, n)$, (10), (11), and (12), compute U and $E^j(\boldsymbol{z}, n)$.

8. Using (14), (16) and (20), update $w^j(\boldsymbol{z}, n)$, and iterate 2-8 until converges.

8. As the mass of entrants and the total mass of entrants are irrelevant to any of the above steps, the total vacancies and the total number of workers increase linearly with the mass of entrants, i.e., $V(M_e) = M_e V(1)$ and $E(M_e) = M_e E(1)$. Thus, M_e can be backed out by the following equation,

$$\theta = \frac{M_e V(1)}{1 - M_e E(1)}$$
$$\Rightarrow M_e = \frac{\theta}{V(1) + \theta E(1)}$$

A.5 From PDV Wages to Flow Wages

Step 1: Rearranging the PDV recursions in Sec. 2.5. For any firm type j covered by Eq. (14),

$$W^j(\boldsymbol{z}, n) = w^j(\boldsymbol{z}, n) + \beta\, \mathbb{E}_{z_i'|z_i}\left[(1 - p_\varsigma^j(\boldsymbol{z}, (1-\zeta)n))\, W^j(\boldsymbol{z}, n^{j,*}(\boldsymbol{z}, (1-\zeta)n))\right]. \quad (39)$$

Hence,

$$w^j(\boldsymbol{z}, n) = W^j(\boldsymbol{z}, n) \;-\; \beta\, \mathbb{E}_{z_i'|z_i}\left[(1 - p_\varsigma^j(\boldsymbol{z}, (1-\zeta)n))\, W^j(\boldsymbol{z}, n^{j,*}(\boldsymbol{z}, (1-\zeta)n))\right]. \quad (40)$$

For risky young firms ry (Eq. (16)),

$$w^{ry}(\boldsymbol{z}, n) = W^{ry}(\boldsymbol{z}, n) - \beta\, \mathbb{E}_{z_i'|z_i}\Big[(1-\varphi)\big(1 - p_\varsigma^{ry}(\boldsymbol{z}, (1-\zeta)n)\big) W^{ry}(\boldsymbol{z}, n^{ry,*}(\boldsymbol{z}, (1-\zeta)n)) \quad (41)$$
$$+\; \varphi\, \mathbb{E}_{z_m}\big(1 - p_\varsigma^{rm}(\boldsymbol{z}, (1-\zeta)n)\big) W^{rm}(\boldsymbol{z}, n^{rm,*}(\boldsymbol{z}, (1-\zeta)n))\Big].$$

Equations (40)–(41) show that w is a *linear operator* applied to the vector of continuation PDVs W across the relevant states. No further structure is required.

Step 2: Applying the model's PDV decomposition. In Sec. 2.7, the PDV wage admits the affine representation

$$W^{\chi} \;=\; \alpha_U\, U(f) \;+\; \alpha_C\, C^{\chi}(f) \;+\; \alpha_P\, P^{\chi}(f) \;+\; \text{const}, \tag{42}$$

with $\alpha_U > 0$ and $\alpha_C < 0$. Substituting (42) (and its analogues for the relevant successor states) into (40)–(41) yields

$$w^{\chi} \;=\; \phi_U\, U(f) \;+\; \phi_C\, C^{\chi}(f) \;+\; \phi_P\, P^{\chi}(f) \;+\; \text{const}', \tag{43}$$

where the coefficients $\phi_{\bullet}$ are linear combinations of $\alpha_{\bullet}$ with weights given by β and the transition kernels in (40)–(41). Linearity of the recursions implies $\text{sgn}(\phi_C) = \text{sgn}(\alpha_C)$ and $\text{sgn}(\phi_P) = \text{sgn}(\alpha_P)$.

Step 3: Slope decomposition for flow wages. Taking the experimenting–non-experimenting difference and differentiating with respect to the job-finding rate f,

$$\frac{\partial}{\partial f}\big(w^1 - w^0\big) \;=\; \underbrace{\phi_C\big(C^{1'}(f) - C^{0'}(f)\big)}_{\text{career-value channel}} \;+\; \underbrace{\phi_P\big(P^{1'}(f) - P^{0'}(f)\big)}_{\text{equilibrium wedge}}. \tag{44}$$

Because $U(f)$ is common across χ, its contribution cancels in the difference. Equation (44) is the exact analogue, for flow wages, of the PDV slope decomposition used in the text.

B Appendix for empirical analysis

B.1 Robustness check

B.1.1 Young firms: less than five years old

Table 5: Experimentation and job finding rate for firms with age < 5

Experimentation	0.00261	0.00211	0.00161	0.00125	0
	(0.00270)	(0.00268)	(0.00268)	(0.00267)	(.)
Job Finding Rate	0.00557***	0.00418***	0.00416***	0.00473***	0.00390***
	(0.00108)	(0.00107)	(0.00107)	(0.00107)	(0.000919)
Exp. × Job Finding Rate	-0.00674***	-0.00601***	-0.00612***	-0.00600***	-0.00454***
	(0.00133)	(0.00132)	(0.00132)	(0.00131)	(0.00121)
Observations	772967	772967	772967	772961	762492
R-squared	0.882	0.883	0.883	0.883	0.922
Time-Varying Worker Controls	No	Yes	Yes	Yes	Yes
Worker FE	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	No	No
Firm FE	No	No	No	No	Yes
Year FE	Yes	Yes	Yes	No	Yes
Year x Industry FE	No	No	No	Yes	No

Notes: This table presents the results for the wage premium at experimenting young firms (defined by firms less than 5 years old) and its interaction with labor market conditions. The sample consists of a matched worker-year panel from 2008 to 2023, with the dependent variable being the log of yearly real hourly wages. Time-varying worker controls include worker age squared, worker age cubed, worker age interacted with education, worker age squared interacted with education and worker age cubed interacted with education. Worker age is log-transformed and normalized by 40, while education is measured in years of study and also log-transformed. In regressions with worker fixed effects, worker age and education are excluded as linear controls since they are collinear with the fixed effects. The job finding rate is calculated as the ratio of all inflows into employment divided by stock of non-employed. Note that the job finding rate is demeaned and divided by the standard deviation, so a unit increase in this rate is interpreted as a change of 1 standard deviation. Standard errors are clustered at the level of firm and worker and reported in parenthesis. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

B.1.2 Experimenting firms: top 1% and bottom 49%

Table 6: Experimentation (top 1% and bottom 49%) and job finding rate

Experimentation	0.0124***	0.0123***	0.0113***	0.0107***	0
	(0.00373)	(0.00373)	(0.00374)	(0.00370)	(.)
Job Finding Rate	0.00480***	0.00372**	0.00372**	0.00485***	0.00351***
	(0.00157)	(0.00156)	(0.00156)	(0.00156)	(0.00129)
Exp. × Job Finding Rate	-0.00584***	-0.00528***	-0.00542***	-0.00622***	-0.00610***
	(0.00172)	(0.00171)	(0.00171)	(0.00163)	(0.00160)
Observations	399053	399053	399053	399038	389738
R-squared	0.900	0.901	0.901	0.901	0.940
Time-Varying Worker Controls	No	Yes	Yes	Yes	Yes
Worker FE	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	No	No
Firm FE	No	No	No	No	Yes
Year FE	Yes	Yes	Yes	No	Yes
Year x Industry FE	No	No	No	Yes	No

Notes: This table presents the results for the wage premium at experimenting (defined by the top 1% and bottom 49% in α_j) young firms and its interaction with labor market conditions. The sample consists of a matched worker-year panel from 2008 to 2023, with the dependent variable being the log of yearly real hourly wages. Time-varying worker controls include worker age squared, worker age cubed, worker age interacted with education, worker age squared interacted with education and worker age cubed interacted with education. Worker age is log-transformed and normalized by 40, while education is measured in years of study and also log-transformed. In regressions with worker fixed effects, worker age and education are excluded as linear controls since they are collinear with the fixed effects. The job finding rate is calculated as the ratio of all inflows into employment divided by stock of non-employed. Note that the job finding rate is demeaned and divided by the standard deviation, so a unit increase in this rate is interpreted as a change of 1 standard deviation. Standard errors are clustered at the level of firm and worker and reported in parenthesis. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

B.1.3 Experimenting firms: top 10% and bottom 40%

Table 7: Experimentation (top 10% and bottom 40%) and job finding rate

Experimentation	0.00270	0.00199	0.00180	0.00229	0
	(0.00361)	(0.00361)	(0.00362)	(0.00358)	(.)
Job Finding Rate	0.00372**	0.00278*	0.00273*	0.00366**	0.00146
	(0.00152)	(0.00151)	(0.00151)	(0.00150)	(0.00127)
Exp. × Job Finding Rate	-0.00475***	-0.00442**	-0.00444**	-0.00493***	-0.00207
	(0.00184)	(0.00184)	(0.00184)	(0.00177)	(0.00173)
Observations	399053	399053	399053	399038	389738
R-squared	0.900	0.900	0.901	0.901	0.940
Time-Varying Worker Controls	No	Yes	Yes	Yes	Yes
Worker FE	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	No	No
Firm FE	No	No	No	No	Yes
Year FE	Yes	Yes	Yes	No	Yes
Year x Industry FE	No	No	No	Yes	No

Notes: This table presents the results for the wage premium at experimenting (defined by the top 10% and bottom 40% in α_j) young firms and its interaction with labor market conditions. The sample consists of a matched worker-year panel from 2008 to 2023, with the dependent variable being the log of yearly real hourly wages. Time-varying worker controls include worker age squared, worker age cubed, worker age interacted with education, worker age squared interacted with education and worker age cubed interacted with education. Worker age is log-transformed and normalized by 40, while education is measured in years of study and also log-transformed. In regressions with worker fixed effects, worker age and education are excluded as linear controls since they are collinear with the fixed effects. The job finding rate is calculated as the ratio of all inflows into employment divided by stock of non-employed. Note that the job finding rate is demeaned and divided by the standard deviation, so a unit increase in this rate is interpreted as a change of 1 standard deviation. Standard errors are clustered at the level of firm and worker and reported in parenthesis. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

B.1.4 Full population (working-age and non–working-age)

Table 8: Experimentation and job finding rate for full population

Experimentation	0.0108***	0.00281	0.00231	0.00287	0
	(0.00296)	(0.00274)	(0.00274)	(0.00263)	(.)
Job Finding Rate	0.0105***	0.00445***	0.00438***	0.00511***	0.00271**
	(0.00134)	(0.00125)	(0.00125)	(0.00124)	(0.00109)
Exp. $\times$ Job Finding Rate	-0.00629***	-0.00420***	-0.00426***	-0.00509***	-0.00275*
	(0.00153)	(0.00151)	(0.00151)	(0.00140)	(0.00154)
Observations	717295	717295	717295	717288	705232
R-squared	0.899	0.908	0.908	0.909	0.944
Time-Varying Worker Controls	No	Yes	Yes	Yes	Yes
Worker FE	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	No	No
Firm FE	No	No	No	No	Yes
Year FE	Yes	Yes	Yes	No	Yes
Year x Industry FE	No	No	No	Yes	No

Notes: This table presents the results for the wage premium at experimenting young firms and its interaction with labor market conditions. The sample consists of a matched worker-year panel from 2008 to 2023, with the dependent variable being the log of yearly real hourly wages. Time-varying worker controls include worker age squared, worker age cubed, worker age interacted with education, worker age squared interacted with education and worker age cubed interacted with education. Worker age is log-transformed and normalized by 40, while education is measured in years of study and also log-transformed. In regressions with worker fixed effects, worker age and education are excluded as linear controls since they are collinear with the fixed effects. The job finding rate is calculated as the ratio of all inflows into employment divided by stock of non-employed. Note that the job finding rate is demeaned and divided by the standard deviation, so a unit increase in this rate is interpreted as a change of 1 standard deviation. Standard errors are clustered at the level of firm and worker and reported in parenthesis. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

B.2 Young-firms wage premia and job finding rates

B.2.1 Empirical strategy

We augment the classical two-way fixed effects model of Abowd et al. (1999) (AKM) to allow for firm-pay policies to vary with firm age and local labor market conditions. Let w_{it} denote the log of the real hourly wage of worker i in year t, who is employed at firm $j = J(i,t)$ in the local labor market—or commuting zone—$m = M(i,t)$. Let $f_{M(i,t)}$ denote the job finding rate from non employment experienced by worker i in her market $M(i,t)$ and $Y_{J(i,t)}$ denote an indicator function that equals 1 if a firm is classified as young (i.e., less than three years old). Note that the job-finding rate $f_{M(i,t)}$ is standardized—i.e., demeaned and divided by its standard deviation—to facilitate interpretation of the coefficients in the regression analysis below. We estimate variants of the following regression:

$$w_{it} = \eta_t + \beta X_{it} + \gamma_1 Y_{J(i,t)} + \gamma_2 f_{M(i,t)} + \delta \left(Y_{J(i,t)} \times f_{M(i,t)} \right) + \epsilon_{it}, \tag{45}$$

where η_t denotes year fixed effects. The vector X_{it} includes worker fixed effects α_i, firm fixed effects $\psi_{J(i,t)}$, and time-varying controls, depending on specifications. These controls comprise log-transformed years of education, and log-transformed age normalized by 40, along with its square and cube. In addition, following Babina et al. (2019), X_{it} includes interaction terms between log education and each of the normalized age terms. The coefficient γ_1 captures the average wage premium at young firms—interpretable as such since the job-finding rate $f_{M(i,t)}$ is demeaned. The key parameter of interest is δ, which measures how this wage difference varies with local labor market conditions.

We test the hypothesis that the wage differential decreases with the higher job finding rates from non-employment, i.e., $\hat{\delta} < 0$. The specification in (45) assumes that the wage negotiated by worker i is determined by the commuting zone where the worker resides, rather than the commuting zone where the firm is located. This aligns with the theoretical model in Section 2, where the job-finding rate, as a worker-side variable, influences the career value of unemployment and thereby affects bargained wages.

In equation (45), worker fixed effects account for the time-invariant component of wages attributable to individual heterogeneity, which is similarly rewarded across employers. This component may arise from factors such as innate ability and other personal characteristics. In contrast, firm fixed effects capture the time-invariant wage component driven by employer heterogeneity, which impacts identically all employees. This could be influenced by differences in productivity, rent-sharing agreements, or workplace amenities. Year fixed effects control for time-varying earnings shifts that affect all workers simultaneously, including changes in wages related to business cycle fluctuations. The set of time-varying worker controls—including squared and cubed terms of age interacted with education—is intended to capture both general human capital accumulation over a worker's career.

B.2.2 Results

Table 9 presents the regression results examining the relationship between wages, young firm status, and local labor market conditions across five specifications. The columns progressively introduce additional controls and fixed effects to address potential sources of heterogeneity.

Table 9: Young firm and job finding rate

Young	-0.0291***	-0.0288***	-0.0263***	-0.0301***	-0.00606***
	(0.00111)	(0.00106)	(0.00101)	(0.000828)	(0.00136)
Job Finding Rate	0.0107***	0.00794***	0.00792***	0.00614***	0.00690***
	(0.000899)	(0.000675)	(0.000655)	(0.000387)	(0.000605)
Young × Job Finding Rate	-0.0107***	-0.0110***	-0.0107***	-0.00912***	-0.00618***
	(0.000983)	(0.000914)	(0.000859)	(0.000703)	(0.000645)
Observations	7730149	7730149	7730148	7730031	7711419
R-squared	0.868	0.871	0.872	0.875	0.895
Time-Varying Worker Controls	No	Yes	Yes	Yes	Yes
Worker FE	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	No	No
Firm FE	No	No	No	No	Yes
Year FE	Yes	Yes	Yes	No	Yes
Year x Industry FE	No	No	No	Yes	No

Notes: This table presents the baseline results for the wage premium at young firms and its interaction with labor market conditions. The sample consists of a matched worker-year panel from 2008 to 2023, with the dependent variable being the log of yearly real hourly wages. Young firms are defined as those less than three years old at the start of a given year. Time-varying worker controls include worker age squared, worker age cubed, worker age interacted with education, worker age squared interacted with education, and worker age cubed interacted with education. Worker age is log-transformed and normalized by 40, while education is measured in years of study and also log-transformed. In regressions with worker fixed effects, worker age and education are excluded as linear controls since they are collinear with the fixed effects. The job finding rate is calculated as the ratio of all inflows into employment divided by stock of non-employed. Note that the job finding rate is demeaned and divided by the standard deviation, so a unit increase in this rate is interpreted as a change of 1 standard deviation. Standard errors are clustered at the level of commuting zones and reported in parenthesis. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

The job finding rate, capturing local labor market conditions, exhibits a strong positive association with wages across all specifications. This relationship underscores the importance of regional labor market strength in shaping wage levels: workers in areas with higher job-finding rates command higher wages.

The interaction between young firm status and the job finding rate—our main object of interest—is consistently negative and highly significant across all specifications in Table 9. This robust finding indicates that the wage premium associated with working at a young firm diminishes when job-finding rates are high—that is, when labor market conditions improve and unemployment becomes less costly.

In Columns 1 through 4, identification comes both from variation across firms of different ages located in different commuting zones, and from within-firm variation over time as firms hire workers residing in different commuting zones. Column 1 presents the specification with worker and year fixed effects, while columns 2, 3, and 4 progressively add a rich set of time-varying worker controls, industry fixed effects, and industry×year fixed effects respectively. These additions help to account for unobserved worker and industry heterogeneity and observable worker-level factors. In essence, the interaction coefficient captures that, across commuting zones, the pay premium for young firms is smaller in areas with higher job-finding rates.

Column 5 introduces firm fixed effects, isolating identification to within-firm, over-time variation across workers in local labor market conditions, based on where workers reside. This is a stricter test: it shows that even within the same firm, the wage differential between workers in labor markets with high and low job-finding rates is smaller when the firm is young. This is consistent with the theoretical insight that greater unemployment safety reduces wages when layoff risk is high—such as when workers are employed by young firms.

When controlling for both worker and firm fixed effects (column 5), a one standard deviation increase in the job finding rate reduces the young-firm wage premium by 0.62 p.p. If the interaction coefficient in column 5 reflects the true effect, the decline in the premium is roughly equal in size to the premium, suggesting that the perceived risk of working at young firms is material.

In the counterfactual experiment of Section 4 where we reduce hiring costs, the model predicts a 21.1% rise in the job-finding rate and a 0.654 p.p. decline in the young-firm wage premium. This corresponds to an elasticity that is about twice as large as the one estimated from the data. However, it is important to note that the model targets unemployment-to-employment transitions, while the empirical measure is based on inflows from non-employment, which include both unemployed and inactive individuals. Since the inactive are typically less responsive to labor market conditions, the empirical elasticity likely understates the true responsiveness. Taking this into account—along with the uncertainty around the estimates—the magnitude implied by the model appears broadly in line with the empirical evidence.

Lastly, we have verified that the results in Table 9 are robust to defining young firms using a five-year threshold (see Table 10).

Table 10: Young firm (age $<$ 5) and job finding rate

Young	-0.0273***	-0.0272***	-0.0247***	-0.0285***	-0.00385**
	(0.00111)	(0.00105)	(0.000982)	(0.000861)	(0.00161)
Job Finding Rate	0.0112***	0.00843***	0.00836***	0.00658***	0.00698***
	(0.000918)	(0.000687)	(0.000666)	(0.000394)	(0.000609)
Young × Job Finding Rate	-0.0103***	-0.0106***	-0.0101***	-0.00841***	-0.00401***
	(0.000919)	(0.000827)	(0.000770)	(0.000679)	(0.000542)
Observations	7730149	7730149	7730148	7730031	7711419
R-squared	0.868	0.871	0.872	0.875	0.895
Time-Varying Worker Controls	No	Yes	Yes	Yes	Yes
Worker FE	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	No	No
Firm FE	No	No	No	No	Yes
Year FE	Yes	Yes	Yes	No	Yes
Year x Industry FE	No	No	No	Yes	No

Notes: This table presents the baseline results for the wage premium at young firms and its interaction with labor market conditions. The sample consists of a matched worker-year panel from 2008 to 2023, with the dependent variable being the log of yearly real hourly wages. Young firms are defined as those less than five years old at the start of a given year. Time-varying worker controls include worker age squared, worker age cubed, worker age interacted with education, worker age squared interacted with education, and worker age cubed interacted with education. Worker age is log-transformed and normalized by 40, while education is measured in years of study and also log-transformed. In regressions with worker fixed effects, worker age and education are excluded as linear controls since they are collinear with the fixed effects. The job finding rate is calculated as the ratio of all inflows into employment divided by stock of non-employed. Note that the job finding rate is demeaned and divided by the standard deviation, so a unit increase in this rate is interpreted as a change of 1 standard deviation. Standard errors are clustered at the level of commuting zones and reported in parenthesis. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.