Safety in Unemployment and Risky Experimentation of Startups*

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Abstract

We develop a theory in which a lower economic cost of unemployment increases workers' willingness to join risky startups, thereby depressing negotiated wages relative to safer firms. These lower wages incentivize endogenous experimentation by young firms, activities that are risky but hold the potential for exceptionally high productivity, ultimately boosting aggregate productivity. Using Danish employer-employee matched data and exploiting geographical variation, we empirically test this mechanism and show that wages at experimenting startups are lower relative to non-experimenting firms in labor markets with higher job-finding rates—a pattern that holds both across firms and within firms that hire workers across multiple local labor markets.

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1 Introduction

High-growth firms—particularly high-growth young firms—play a pivotal role in driving aggregate productivity (Haltiwanger et al., 2016). A growing body of research emphasizes that firms are heterogeneous from birth, and that their subsequent growth is largely driven by these *ex-ante* characteristics, such as business ideas and growth motives (Hurst and Pugsley, 2011; Sterk et al., 2021). Breakthrough business ideas often emerge from experimentation, which is inherently risky but can yield exceptionally high productivity. Understanding the conditions under which new firms endogenously choose to pursue such high-risk, high-reward strategies is therefore crucial. In this paper, we shift the focus from the aggregate implications of high-growth young firms to understanding the conditions that lead such firms to emerge in the first place.

Specifically, we emphasize how labor market conditions can influence the willingness of new firms to engage in risky experimentation. Entrepreneurs are not the only ones who bear risk; workers joining young firms also face risk, as they may be laid off if experimentation fails. When unemployment is less costly—due to higher job-finding rates—workers are more willing to accept positions at risky startups. This increased willingness lowers the wages such firms must offer relative to safer firms. The resulting reduction in relative labor costs makes experimentation more attractive, increases the share of entrants pursuing high-upside strategies, and raises aggregate productivity. We refer to this mechanism, whereby an increase in the job finding rate leads to a fall in the relative wage of risky startups as the "unemployment-safety" channel.

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). In particular, we illustrate—both analytically and through model simulations—the unemployment-safety channel as a *propagation* mechanism whereby labor market institutions, by influencing the job-finding rate, shape the relative wages offered by experimenting versus non-experimenting firms.[1]

A central ingredient of this mechanism is the role of the AOB, which links job

[1]We refer to the unemployment-safety channel as a propagation mechanism because the job-finding rate is an endogenous object; an exogenous change in labor market institutions is therefore required to trigger a change in the job-finding rate. Later, we show how quantitatively important this channel is in determining the aggregate productivity effects of changes in labor market institutions.

finding rates to negotiated wages through the value of unemployment. Unlike Nash bargaining, where the threat point is immediate match destruction, the AOB framework models the threat point as a delay in reaching agreement: firms incur delay costs, and workers prefer immediate agreement due to discounting. We show that, in this setting, wages at risky firms unambiguously fall relative to safe firms when the value of unemployment increases, as workers at risky firms—who face a higher risk of layoff—benefit disproportionately from improvements in the value of unemployment. The AOB assumption is crucial: under standard Nash bargaining, firm surplus and negotiated wages respond to changes in job finding rates uniformly across firms, regardless of the risk of job loss. As a result, the unemployment-safety channel we highlight cannot emerge under Nash bargaining.

Equipped with a model calibrated to the Danish economy, we quantify the importance of the unemployment-safety channel as a propagation mechanism in response to changes in labor market institutions. In particular, we use changes in firms' job creation costs as an important illustrative scenario, 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.[2] 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 startups 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

[2]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).

productivity. Overall, productivity increases by approximately 1%.

To isolate the importance of the unemployment-safety propagation channel, 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 startups, so the share of entrants undertaking risky experimentation remains nearly unchanged—highlighting the central role of the safety 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 safety 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–safety channel. The theory implies that a higher value of unemployment—proxied empirically by commuting–zone job–finding rates—weakens workers' effective threat point more strongly at firms that are actively experimenting, lowering their negotiated wages relative to non-experimenting ("safe") young firms. We operationalize this prediction in Danish matched employer–employee data (2008–2023) by constructing a model-consistent firm-level measure of experimentation from the permanent component of sales-growth residuals, estimated within industry–entry cohorts. Intuitively, the model maps experimentation to higher dispersion in ex-post permanent productivity; empirically, we recover each firm's permanent growth type and classify "experimenting" firms as the tail types of that distribution, treating the remainder as safe.

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 labor-market safety improves. 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 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 used for identification, but they support the construct validity of our model-consistent classification.

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 any 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, only entrants/young firms undertake experimentation and thus carry higher separation risk; as firms mature, uncertainty resolves and the associated pay premium vanishes. Hence the model predicts that greater labor-market safety (higher job-finding) decreases the young–mature wage differential. The interaction of a young-firm dummy with the job-finding rate is negative and statistically 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 more indirectly and with attenuation from aggregation, the main experimenting-vs.-safe result discussed above.

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) show 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 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-safety 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 provide safety to workers 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 new firms share the same initial permanent component of productivity, z_e. With an exogenous per-period probability φ, a young firm loses its young-firm status and becomes a mature firm.[4] When a young firm becomes mature, it draws a new permanent component of productivity from the distribution $z_m \sim \Pi(z_m)$. Lastly, in every period, all firms are subject to persistent temporary productivity shocks, z_i, which are initialized at the same value for new entrants.

Upon entry, firms choose between two business models, represented by distinct distributions over permanent productivity shocks $\Pi(z_m)$: in the safe business model, the distribution is degenerate, with the draw of productivity being equal to the entrant firm's initial productivity, z_e; in the risky business model, the distribution allows for a continuum of outcomes, including the potential to become a superstar firm:

$$\Pi(z_m) = \begin{cases} \mathbb{1}_{z_m = z_e} & \text{if startups choose to be safe} \\ \Pi_R(z_m) & \text{if startups choose to bet} \end{cases}$$

We assume that the support of $\Pi_R(z_m)$ has a lower bound below and an upper bound above z_e, capturing the idea that the risky business model can lead to both worse and better outcomes compared to the safe business model. Throughout the paper, we

[4] φ is calibrated so that the average duration as a young firm, $1/\varphi$, matches 3 years, consistent with the definition of young firms in the empirical analysis.

refer to young firms that choose the risky business model as experimenting firms or 'startups'—that is, newly established businesses pursuing innovative strategies under significant uncertainty. While the term is often associated with the technology sector, our usage is broader and sector-neutral: through the lens of our framework, any young firm engaging in high-upside experimentation qualifies as a startup, regardless of industry.

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 firm behavior 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.

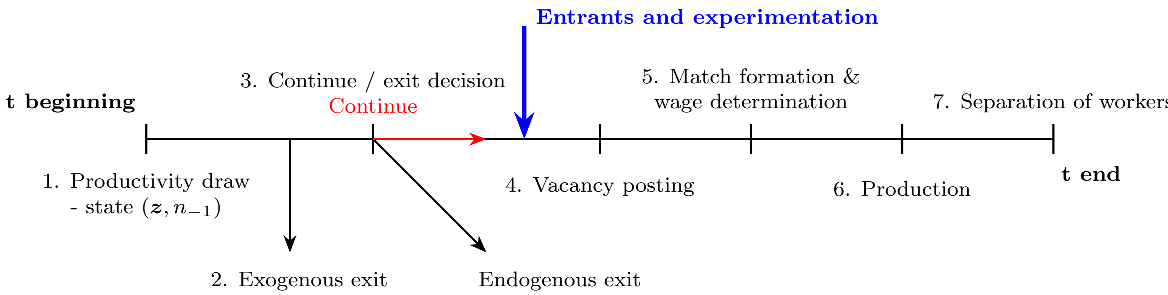
Firms face decreasing returns to scale, and employ labor as the only factor of production. The labor market is frictional, so firms need to post vacancies in order to hire workers. We assume a unit measure of identical workers, who can be either employed or unemployed. Unemployed workers receive unemployment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

Figure 1: Timing



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, and production takes place. 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 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 $M(u_0, v) = m u_0^{\omega} v^{1-\omega}$, 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 is expanding its workforce; firing workers is 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 startups*, 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:

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

$$\text{subject to} \quad \Delta n \mathbb{1}_+ = (n - n_{-1})\mathbb{1}_+ = vq(\theta),$$

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:

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

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:[5]

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

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

[5] 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).

marginal returns and costs of hiring are equalized:

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

2.5 Workers

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

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

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

$$\begin{aligned} E^j(\boldsymbol{z}, n) = w^j(\boldsymbol{z}, n) + \beta \mathbb{E}_{z_i'|z_i} \Big[& p^j_\varsigma(\boldsymbol{z}, (1-\zeta)n) \cdot U' \\ & + \left(1 - p^j_\varsigma(\boldsymbol{z}, (1-\zeta)n)\right) \cdot E^j(\boldsymbol{z}, n^{j,*}(\boldsymbol{z}, (1-\zeta)n)) \Big], \quad \text{for } j \in \{s, rm\} \end{aligned} \tag{11}$$

where $p^j_\varsigma(\boldsymbol{z}, (1-\zeta)n)$ 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.[6]

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

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

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

where a worker continues the match if: they are not exogenously separated $(1-\zeta)$; the firm does not exit exogenously $(1-\eta)$ or endogenously $(1-p^j_x)$; 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., $\min\left(\frac{n^{j,*}}{(1-\zeta)n}, 1\right)$.

corresponding adjustments to future employment values and separation risk:

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

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:

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

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

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

and the subsequent career value is:

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

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

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

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

Since the career value of workers in risky startups 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 key advantages over standard Nash bargaining. First, as demonstrated by Hall and Milgrom (2008), it addresses the limitations of the standard search-and-matching model in generating strong labor market responses to productivity shocks. Second, Christiano et al. (2016) show that general equilibrium models incorporating this protocol better capture macroeconomic dynamics over the business cycle compared to numerous alternative assumptions. Third, Jäger et al. (2024) find that this protocol produces realistic elasticities of negotiated wages with respect to unemployment benefits, unlike standard Nash bargaining. This feature is critical for our analysis, as it disciplines how the value of unemployment feeds into negotiated wages—a key object in our quantitative evaluation. Most importantly for our purposes, as we explain in Section 2.7 below, Nash bargaining is not well suited to capture the unemployment-safety channel that is central to our analysis.

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 $W^j_k(\boldsymbol{z}, n)$ for $j \in \{s, ry, rm\}$, respectively. The condition that makes a worker indifferent between accepting and rejecting the firm's offer is:

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

where $E^j(\boldsymbol{z}, n)$ and $E^j_k(\boldsymbol{z}, n)$ are the values to a worker in firm $(\boldsymbol{z}, n)$ when the present discounted value of wages are $W^j(\boldsymbol{z}, n)$ and $W^j_k(\boldsymbol{z}, n)$, 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:

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

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 $W^j(\boldsymbol{z},n)$:

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

Lastly, we derive the flow wage $w^j(\boldsymbol{z},n)$ that is consistent with (14) and (20).[7]

2.7 Discussion: The unemployment-safety 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, which feeds into the wage bargaining process and alters the relative wages offered by risky startups 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 startups 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 startups than in safe or risky mature firms. Comparing the effects between risky startups and safe firms, in Eq. (15) and (17), under the assumption of a

[7]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).

stationary equilibrium where $U' = U$, one can see that:

$$\frac{\partial C^{ry}(\boldsymbol{z}, n)}{\partial U} > \frac{\partial C^{s}(\boldsymbol{z}, n)}{\partial U},$$

$$\text{when } \; (1-\varphi) p_{\varsigma}^{ry}(\boldsymbol{z}, (1-\zeta)n) + \varphi \mathbb{E}_{z_m} p_{\varsigma}^{rm}(\boldsymbol{z}, (1-\zeta)n) > p_{\varsigma}^{s}(\boldsymbol{z}, (1-\zeta)n), \tag{21}$$

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 startup firms relative to safe firms, i.e., $\frac{d\frac{W^{ry}}{W^s}}{df} < 0$.

4. Due to lower present-value wages at risky startups, 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, negotiated present-value wages in equation (20), are shaped by two opposing forces. First, the value of unemployment enters directly as a fallback option if negotiations break down with probability δ_b, which tends to raise wages. Second, a higher value of unemployment increases the value of employment—that is, the overall value of staying in the job, which includes both future wages, W, and the possibility of future unemployment, C. The increase in C makes workers more eager to reach agreement quickly, since delaying would yield a discounted continuation value. 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, workers in risky firms place greater value on securing the future contingencies embedded in the employment relationship, and are thus more willing to settle early. This weakens their effective threat point in bargaining and results in a decline in present-value wages relative to workers in safer firms.

AOB versus Nash. We adopt alternating–offer bargaining (AOB) instead of Nash bargaining because the latter hardwires unit elasticities of worker and firm surpluses with respect to the job-finding rate—that is, these elasticities are *invariant* to firm type and to differences in match-destruction rates, muting the impact of job finding rates on experimentation decisions. A second reason is that the two frameworks have distinct implications for *current* wages, the object we observe in the data. Under Nash bargaining, current wages respond uniformly across firms to changes in the value of unemployment, regardless of job-loss probability. By contrast, under AOB, as shown numerically in the comparative-static exercise of Table 2, the same differential response derived analytically for present-value wages also holds for current wages. As we test in the data in Section 5, the wage differential between risky and safe firms aligns closely with the AOB prediction.

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 $\Pi_R(z_m)$ 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 bargaining discount factor, β_b, is set to $0.99^{1/90}$, reflecting daily bargaining. 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.

Three parameters—δ_b, c_σ, and σ_σ—warrant special attention, as they are central to our mechanism. 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 wage sensitivity to changes in the value of unemployment. Jäger et al. (2024) provide careful estimates of the 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 cost of risky experimentation, c_σ, is calibrated to match the share of non-experimenting entrepreneurs. Hurst and Pugsley (2011) show that between one-third and one-half of entrepreneurs do not intend to bring new products or services to the market. We take this to imply that roughly 50% of firms are non-experimenting and use it as a target moment. Lastly, the scale of taste shocks for the safe option, σ_σ, is calibrated to match the coefficient from a regression of young firm shares on the job-finding rate

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 startups		
β_b	Discount rate (bargaining)	$0.99^{1/90}$	Daily bargaining		
ρ_t	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 (startups)	0.054	0.067
z_e	Entrants' productivity	1.419	Rel. size of mature to startups	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. (2024))	0.031	0.030
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

across Danish regions.[8] If the scale parameter is large—implying that non-pecuniary motives dominate—then, in our model, increases in the job-finding rate have little effect on the share of experimenting firms. This moment is thus informative in identifying 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. (2024), 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

[8] Details on the construction of these variables are provided in Section 5.

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 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 startups 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

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.

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.[9] 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) is defined as Y/N^{α} and can be decomposed as follows:

[9] 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.

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

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 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,

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.

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. Most of the improvement now comes 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.

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.

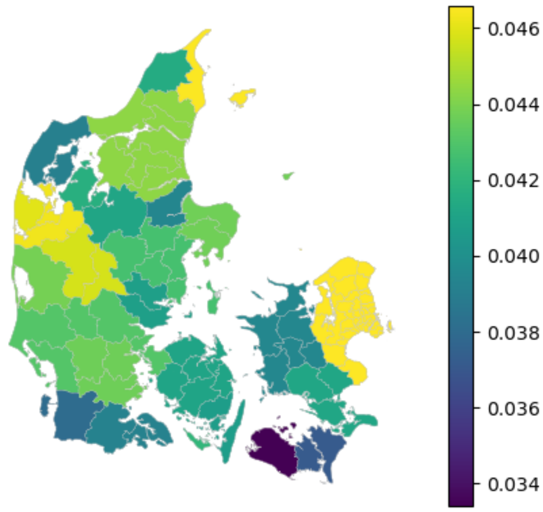
Population Registry: *Befolkningen* (BEF) is an individual-level dataset that includes information such as date of birth, gender, address, civil status, and more. We use the residential address data to map workers to their commuting zones, utilizing a mapping provided by Danmarks Statistics (DST), which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

Figure 2: Job finding rate by 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.

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

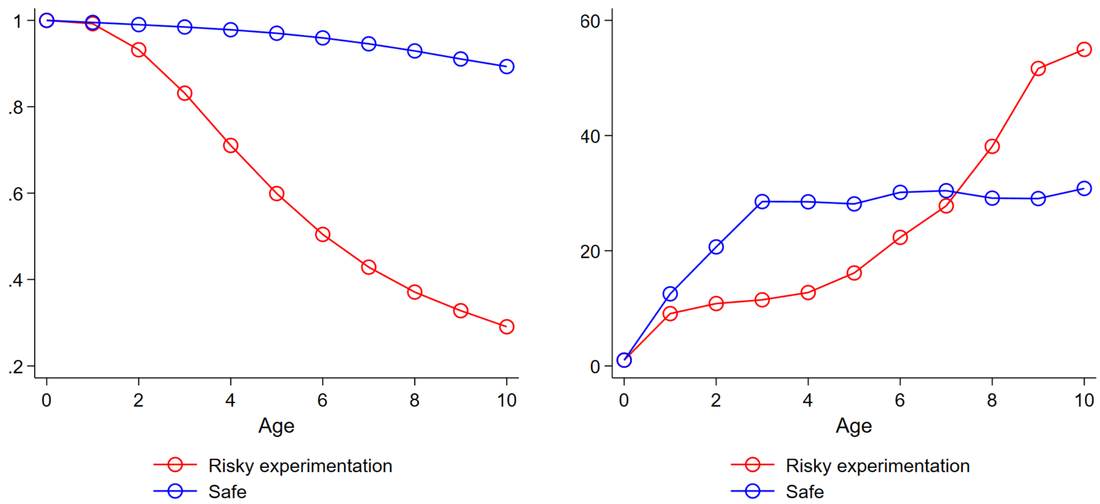
To test the key mechanism, we construct a model-consistent measure of risky experimentation at the firm level. In the model, firms engaged in risky experimentation draw their permanent productivity from a Pareto distribution, which generates more dispersed business outcomes than those of safe entrants. 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.

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



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 *untargeted* by the wage-regression specification in 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:

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

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 the vector X_{it} comprises worker fixed effects, firm fixed effects, and time-varying controls depending on the specification. These controls include worker tenure, log-transformed years of education, and log-transformed age normalized by 40 (along with its square and cube). Following Babina et al. (2019), X_{it} also includes interactions between log education and each of the normalized age terms.

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. This muted estimate likely reflects the coexistence of two offsetting forces. On one hand, as in Michelacci and Quadrini (2005), financially constrained firms may "borrow from employees," offering initially lower wages in exchange for future upside once uncertainty resolves—tending to produce a negative wage differential. On the other hand, workers may demand a compensating risk premium to join firms undertaking uncertain, high-variance projects, pushing wages upward. Our model abstracts from the Michelacci–Quadrini borrowing channel, but it would naturally operate in the data, partially offsetting the upward pressure on wages predicted by the risk-premium mechanism and explaining why the estimated coefficient 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

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.

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 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 behind this result differs by column. In columns 1–3, which do not include firm fixed effects, identification relies on both within-firm and across-firm variation: firms that hire workers in commuting zones with higher job-finding rates tend to offer lower wages if they are more experimental. Column 3 introduces industry fixed effects, ensuring that identification comes from variation within industries across locations. This controls for persistent wage differences across industries, allowing us to identify whether, within a given industry, more experimental firms in high job-finding regions offer lower wages.

In column 4, we absorb year-by-industry fixed effects, meaning the result is now identified off within-industry cross-sectional differences in experimentation and job-finding rates in a given year. This is important because industries differ in how cyclically sensitive their revenues and labor demand are—some may respond more strongly to changes in local employment conditions than others. By controlling for industry-year effects, we ensure that the interaction coefficient is not confounded by such heterogeneous cyclical responses and instead reflects variation in wage premia due to experimentation conditional on these industry-specific business cycle dynamics.

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 (or wage discounts are amplified) 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 supports the mechanism in our 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.

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 risk—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. It is "indirect" because, in the model, experimentation takes place only at entry and the associated risk diminishes as firms age. Comparing wages between young and mature firms therefore offers a model-consistent but less direct test of the same prediction, exploiting a dimension—firm age—that is systematically related, though not perfectly aligned, with the presence of experimentation risk. 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.

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

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

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.

6 Conclusion

This paper proposes a novel mechanism that links worker safety in unemployment to aggregate productivity through the risky experimentation of new entrants. We develop a heterogeneous firm dynamics model in which entrants engage in risky experimentation within a frictional labor market featuring AOB. Our results show that increased job-finding rates for unemployed workers lead to a larger share of entrants undertaking risky experimentation, which, in turn, boosts aggregate 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. This supports our theoretical prediction that greater labor market safety encourages risky experimentation and enhances long-run productivity.

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APPENDIX TO

Safety in Unemployment and Risky Experimentation of Startups

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:

$$\Gamma'_s((z_e, z'_i), n) = \int \int_{n=(1-\zeta)n^{s,*}((z_e,z_i),n_{-1})} (1-\eta)(1-p^s_x((z_e, z'_i), n)) d\Pi(z'_i|z_i) d\Gamma_s((z_e, z_i), n_{-1}) + (1 - P(R)) M_e \mathbb{1}_{n=1} \mathbb{1}_{z'_i=\mu_{z_i}}). \tag{26}$$

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:

$$\Gamma'_{rm}((z_m, z'_i), n) = \int \int_{n=(1-\zeta)n^{rm,*}((z_m,z_i),n_{-1})} (1-\eta)(1-p^{rm}_x((z_m, z'_i), n)) d\Pi(z'_i|z_i) d\Gamma_{rm}((z_m, z_i), n_{-1}) + \int \int_{n=(1-\zeta)n^{rs,*}((z_e,z_i),n_{-1})} \varphi(1-\eta)(1-p^{rm}_x((z_m, z'_i), n)) d\Pi_R(z_m) d\Pi(z'_i|z_i) d\Gamma_{rs}((z_e, z_i), n \tag{27}$$

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

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

$$\Gamma'_{ry}((z_e, z_i'), n) = \int\int_{n=(1-\zeta)n^{ry,*}((z_e,z_i),n_{-1})} (1-\varphi)(1-\eta)(1-p_x^{ry}((z_e, z_i'), n))d\Pi(z_i'|z_i)d\Gamma_{ry}((z_e, z_i), n_{-1}) + P(R)M_e \mathbb{1}_{n=1}\mathbb{1}_{z_i'=\mu_{z_i}}. \tag{28}$$

A.2 Labor market clearing

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

$$u + \int n^{s,*}(\boldsymbol{z}, n_{-1})\, d\Gamma_s(\boldsymbol{z}, n_{-1}) + \int n^{ry,*}(\boldsymbol{z}, n_{-1})\, d\Gamma_{ry}(\boldsymbol{z}, n_{-1}) + \int n^{rm,*}(\boldsymbol{z}, n_{-1})\, d\Gamma_{rm}(\boldsymbol{z}, n_{-1}) = 1, \tag{29}$$

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:

$$\theta = \frac{\int v^{s,*}(\boldsymbol{z}, n_{-1})\, d\Gamma_s(\boldsymbol{z}, n_{-1}) + \int v^{ry,*}(\boldsymbol{z}, n_{-1})\, d\Gamma_{ry}(\boldsymbol{z}, n_{-1}) + \int v^{rm,*}(\boldsymbol{z}, n_{-1})\, d\Gamma_{rm}(\boldsymbol{z}, n_{-1})}{u_0}, \tag{30}$$

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 startups, 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 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.4 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),

$$W^j(\boldsymbol{z}, n) = w^j(\boldsymbol{z}, n) + \beta\, \mathbb{E}_{z_i'|z_i}\big[(1 - p_\varsigma^j(\boldsymbol{z}, (1-\zeta)n))\, W^j(\boldsymbol{z}, n^{j,*}(\boldsymbol{z}, (1-\zeta)n))\big]\,. \quad (31)$$

Hence,

$$w^j(\boldsymbol{z}, n) = W^j(\boldsymbol{z}, n) \;-\; \beta\, \mathbb{E}_{z_i'|z_i}\big[(1 - p_\varsigma^j(\boldsymbol{z}, (1-\zeta)n))\, W^j(\boldsymbol{z}, n^{j,*}(\boldsymbol{z}, (1-\zeta)n))\big]\,. \quad (32)$$

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

$$w^{ry}(\boldsymbol{z}, n) = W^{ry}(\boldsymbol{z}, n) - \beta\, \mathbb{E}_{z_i'|z_i}\Big[(1-\varphi)\big(1 - p_\varsigma^{ry}(\boldsymbol{z}, (1-\zeta)n)\big) W^{ry}(\boldsymbol{z}, n^{ry,*}(\boldsymbol{z}, (1-\zeta)n)) \quad (33)$$
$$+\; \varphi\, \mathbb{E}_{z_m}\big(1 - p_\varsigma^{rm}(\boldsymbol{z}, (1-\zeta)n)\big) W^{rm}(\boldsymbol{z}, n^{rm,*}(\boldsymbol{z}, (1-\zeta)n))\Big].$$

Equations (32)–(33) 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

$$W^{\chi} \;=\; \alpha_U\, U(f) \;+\; \alpha_C\, C^{\chi}(f) \;+\; \alpha_P\, P^{\chi}(f) \;+\; \text{const}, \tag{34}$$

with $\alpha_U > 0$ and $\alpha_C < 0$. Substituting (34) (and its analogues for the relevant successor states) into (32)–(33) yields

$$w^{\chi} \;=\; \phi_U\, U(f) \;+\; \phi_C\, C^{\chi}(f) \;+\; \phi_P\, P^{\chi}(f) \;+\; \text{const}', \tag{35}$$

where the coefficients $\phi_\bullet$ are linear combinations of $\alpha_\bullet$ with weights given by β and the transition kernels in (32)–(33). Linearity of the recursions implies $\operatorname{sgn}(\phi_C) = \operatorname{sgn}(\alpha_C)$ and $\operatorname{sgn}(\phi_P) = \operatorname{sgn}(\alpha_P)$.

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

$$\frac{\partial}{\partial f}\big(w^1 - w^0\big) \;=\; \underbrace{\phi_C\big(C^{1\prime}(f) - C^{0\prime}(f)\big)}_{\text{career-value channel}} \;+\; \underbrace{\phi_P\big(P^{1\prime}(f) - P^{0\prime}(f)\big)}_{\text{equilibrium wedge}}. \tag{36}$$

Because $U(f)$ is common across χ, its contribution cancels in the difference. Equation (36) 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. × 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:

$$w_{it} = \eta_t + \beta X_{it} + \gamma_1 Y_{J(i,t)} + \gamma_2 f_{M(i,t)} + \delta \left(Y_{J(i,t)} \times f_{M(i,t)}\right) + \epsilon_{it}, \tag{37}$$

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 (37) 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 (37), 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 startups 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 $\times$ 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.