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, threat points coincide with outside options, implying that negotiated wages respond to the value of unemployment 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, providing a rationale for modeling them through a unified cost of job creation (Hopenhayn and Rogerson (1993), Pries and Rogerson (2005)).[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 identify institution-specific effects, but to isolate and analyze a common propagation mechanism—namely, how any institution that influences the job-finding rate, and the value of unemployment more broadly, affects 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

[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).

higher wages at safer firms. The resulting shift in relative wages encourages a greater share of entrants to pursue risky experimentation, further contributing to aggregate productivity. Overall, productivity increases by approximately 1%.

To isolate the importance of 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.

In order to provide direct empirical evidence for the job safety channel, we leverage matched employer-employee microdata from Danish administrative records to test whether variation in local labor market conditions correlates with wage differentials in line with the model's predictions. The model generates two key empirical hypotheses. First, since only young firms can engage in risky experimentation—while mature firms are effectively 'safe,' even if they initially pursued a risky strategy—the model predicts that wages at young firms decline relative to those at mature firms as job-finding rates increase.[3] Second, among young firms, those that actively pursue experimental business models—i.e., those with greater upside but higher failure risk—should also face wage differentials that that correlate negatively with local job finding rates. We examine both implications using high-resolution longitudinal microdata.

The Danish data span 2008–2023 and track millions of careers across young and mature firms in 29 commuting zones. To test the first hypothesis, we estimate a model in the spirit of Abowd et al. (1999) (AKM), controlling for permanent worker and firm heterogeneity. We extend the model by interacting a young-firm indicator with the local job-finding rate in the worker's commuting zone, enabling us to assess how the young-firm wage premium varies with local labor market conditions. The estimates reveal a significant and robust negative relationship: the wage premium paid by young firms relative to mature firms declines as job-finding rates increase.

[3] Although extreme, the assumption that only young firms engage in experimentation is broadly consistent with Acemoglu et al. (2018), who show that the R&D intensity of young firms is higher than that of older firms.

This pattern holds both across and within firms. Across firms, young firms in high job-finding areas pay relatively lower wages compared to their mature counterparts. Within firms—where young firms hire workers from multiple local labor markets—the wage differential between workers from high and low job-finding areas increases as the firm ages, reflecting the diminishing role of the unemployment safety channel for mature firms. To the best of our knowledge, we provide the first empirical estimates of how the young-firm pay differentials vary with local labor market conditions.

To test the second hypothesis, we restrict the sample to young firms and classify them by their degree of business experimentation, using firm-level measures based on realized sales growth volatility—an ex-post indicator informative of the degree of risk-taking. Within this subset, we estimate how wage differentials between more and less experimental young firms correlate with local job-finding rates. The results reveal a clear pattern: wages at experimenting firms are significantly lower relative to non-experimenting firms in labor markets with higher job-finding rates. These correlations are also robust both across firms operating in different labor markets and within firms, by comparing wages of workers employed at the same firm, but residing in markets with different unemployment duration.

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.[4] 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.

[4] 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 present a model with heterogeneous multi-worker firms and a frictional labor market, building on Elsby and Michaels (2013), in which wages are determined through alternating-offer bargaining. We begin by describing the economic environment and the structure of the labor market, followed by the characterization of firm and worker value functions and the wage bargaining process. 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 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.[5] 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 equaling 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 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,

[5] 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.

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.

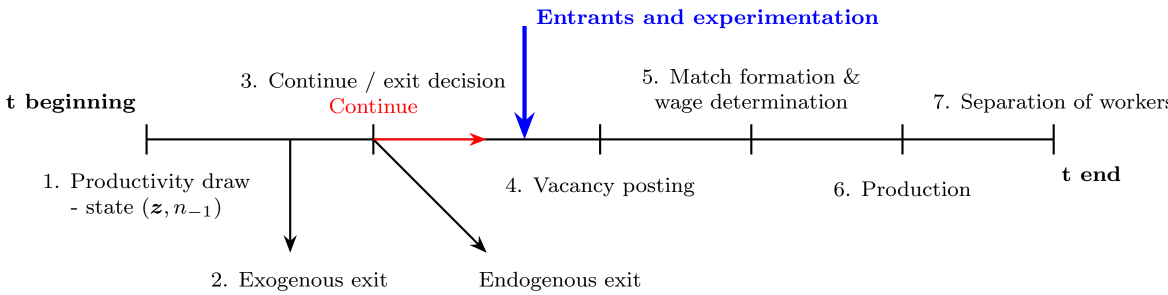
2.2 Timing

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 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

Figure 1: Timing



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:

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

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:

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

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:[6]

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

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

[6] To maintain tractability, we abstract from intrafirm bargaining assuming 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:

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

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

Let E denote the value of employment to a worker. For a worker employed at a safe or risky mature firm, this value is:

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

where $p_\varsigma^j(\boldsymbol{z}, (1-\zeta)n)$ denotes the endogenous separation probability, which accounts for all sources of job loss—exogenous separations, firm exits (both exogenous and endogenous), and layoffs. The term $n^{j,*}(\boldsymbol{z}, (1-\zeta)n)$ represents the firm's optimal labor demand in the next period, conditional on survival and after accounting for separations.[7]

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

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

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

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

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, the unemployment-safety channel central to our analysis cannot operate under Nash bargaining. This is because Nash bargaining ties threat points to outside options, implying that wages respond to the value of unemployment uniformly across firms, irrespective of their risk of job loss. In contrast, under AOB, wage outcomes reflect the costs of delay, which vary with firm-specific separation risk. This distinction is essential for generating the differential wage responses across firms that drive our mechanism, as discussed further in Section 2.7.

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 (small) 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:

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

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

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

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

Lastly, we derive the flow wage $w^j(\boldsymbol{z}, n)$ that is consistent with (14) and (20).[8]

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 $E^j(\boldsymbol{z}', n') \geq U$; 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

[8] 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).

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

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

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

which holds under our calibration.

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

4. Due to lower 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 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 wages relative to workers in safer firms.

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-ambitious 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-ambitious 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 across Danish regions.[9] 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 young 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

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

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-ambitious 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

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.

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.

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 both greater productivity and the increased value of unemployment. The decline in relative wages at risky firms raises the share of entrants choosing to experiment by roughly 10 p.p., which in turn leads to an increase in overall firm entry. Greater experimentation raises the failure rate among young firms when they become mature and increases firm exit. As a result, fewer firms survive to maturity, raising both the share of young firms in the economy and their share of total employment.

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

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

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

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

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

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

ity. 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 a reduction in average firm size, as increased experimentation leads more firms to exit. Additionally, the new steady state features a larger share of experimenting firms, which exhibit more dispersed ex-post permanent productivity. The combination of this increased dispersion and labor market frictions leads to greater misallocation, reducing aggregate productivity by about 0.3%.

To assess how much the propagation channel of interest contributes to the overall increase in productivity of 1%, we recompute aggregate productivity and its decomposition while holding the value of unemployment constant (Column "Low χ_0, fixed U"). In this counterfactual, aggregate productivity still rises—by approximately 0.6%—indicating that the unemployment safety channel accounts for the remaining 0.4%. Most interestingly, the composition of gains differs markedly from the baseline scenario. 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.

Testable Implications The model experiments above show 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

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.

from bargaining: workers in risky young firms, which are still subject to experimentation risk, accept lower wages compared to those in safe firms or in risky firms that have matured. From this mechanism, we derive two testable implications:

- Higher job-finding rates for the unemployed should be negatively associated with the wage differential between young and mature firms.
- 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 these implications 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 (i) whether the wage differential between young and mature firms declines with job-finding rates, and (ii) whether, among young firms, wages are lower in experimenting firms relative to non-experimenting ones when job-finding rates are higher.

While the first test examines how the average wage premium for young firms varies with local job-finding rates, it aggregates across heterogeneous young firms—some engaging in risky experimentation, others not. In our model, it is specifically the decline in wages among young experimenting firms—driven by more favorable labor market conditions—that pulls down the average wage for young firms overall. In contrast, wages in young safe firms rise. Thus, the second test, which compares wages between experimenting and non-experimenting young firms, provides a more direct test of the mechanism. However, implementing it requires classifying firms by experimentation status—an empirical step that introduces potential measurement error. In this sense, the first approach offers a simpler, more transparent test, albeit a more indirect one, while the second offers sharper identification of the mechanism at the cost of relying on constructed measures that introduce estimation-driven measurement error.

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.

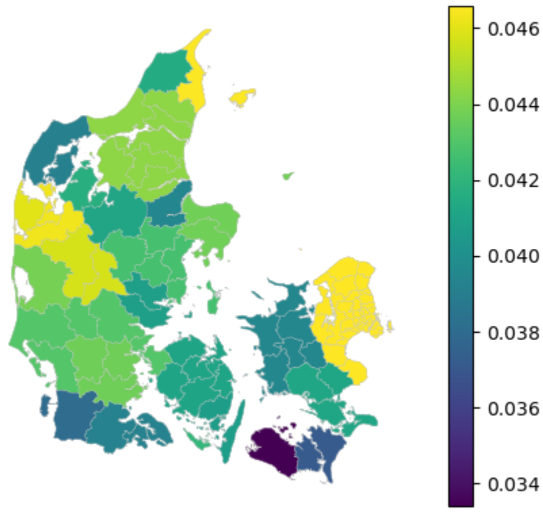
Population Registry: *Befolkningen* (BEF) is an individual-level dataset that includes information such as date of birth, gender, address, civil status, and more. We use the residential address data to map workers to their commuting zones, utilizing a mapping provided by Danmarks Statistics (DST), which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

5.2.1 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:

$$w_{it} = \eta_t + \beta X_{it} + \gamma_1 Y_{J(i,t)} + \gamma_2 f_{M(i,t)} + \delta \left(Y_{J(i,t)} \times f_{M(i,t)} \right) + \epsilon_{it}, \tag{23}$$

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 firm size, worker tenure, 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 (23) 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 (23), 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, along with measures of tenure—is intended to capture both general and firm-specific human capital accumulation over a worker's career.

5.2.2 Results

Table 4 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.

The job finding rate, or employment inflow 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 results indicate a negative wage premium prior to the inclusion of time-varying worker and firm controls, reflecting the fact that younger firms pay lower wages. This pattern, shown in column 1, mirrors the raw data evidence discussed in Appendix B.1, where unconditional comparisons reveal that workers in young firms earn significantly less than those in mature firms. This is in line with findings from the U.S. labor market, where younger firms are found to face greater financial constraints (Brown and Medoff, 2003) and attract workers with lower earning potential (Babina et al., 2019).

Column 2 introduces worker fixed effects, which absorb all time-invariant individual heterogeneity. The coefficient on young firm status shrinks substantially—by more than two-thirds—suggesting that much of the raw wage penalty reflects sorting:

Table 4: Regression results

Young	-0.0901***	-0.0263***	0.00296**	0.00142**	0
	(0.00617)	(0.00166)	(0.00134)	(0.000561)	(.)
Job Finding Rate	0.0569***	0.0136***	0.00850***	0.00679***	0.00353***
	(0.0131)	(0.00135)	(0.00138)	(0.00126)	(0.000695)
Young × Job Finding Rate	-0.0144***	-0.00301***	-0.00452***	-0.00658***	-0.00138*
	(0.00276)	(0.000562)	(0.000989)	(0.00158)	(0.000790)
Observations	16,169,311	15,722,215	15,677,334	15,654,518	15,301,911
R-squared	0.0149	0.831	0.859	0.881	0.907
Worker & Firm Controls	No	No	Yes	Yes	Yes
Worker FE	No	Yes	Yes	Yes	Yes
Firm FE	No	No	No	Yes	No
Year FE	Yes	Yes	Yes	Yes	No
Year x Firm FE	No	No	No	No	Yes

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 and firm controls include worker age squared, worker age cubed, worker age interacted with education, worker age squared interacted with education, worker age cubed interacted with education, firm size, firm size squared, firm size cubed, and worker tenure at the firm. Worker age is log-transformed and normalized by 40, while education is measured in years of study and also log-transformed. Firm size is measured as the log of the number of workers, and worker tenure represents the total years of employment at the firm. 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.

workers who select into younger firms tend to earn less for reasons unrelated to firm age per se. Column 3 adds time-varying worker and firm controls, including tenure, firm size, and age-education interactions. The coefficient on young firm status not only diminishes further but reverses sign and becomes positive and significant. This implies that, conditional on worker characteristics and firm observables, young firms actually pay slightly more than mature firms. This is consistent with the idea that young firms must offer compensating wage premia to attract and retain workers, especially when they face elevated uncertainty or limited track records, as suggested by Babina et al. (2019) and Kim (2025).

Column 4 also includes firm fixed effects, holding constant all time-invariant firm characteristics. The premium remains positive and significant, reinforcing the interpretation that younger firms do not necessarily pay less once worker and firm heterogeneity are taken into account. Finally, column 5 includes firm-by-year fixed effects, which absorb all time-varying firm-specific shocks or wage policies, rendering the young-firm indicator unidentified.

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 4. 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 3, 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 raw specification, while columns 2 and 3 progressively add worker fixed effects and a rich set of time-varying worker and firm-level controls, respectively. These additions help to account for unobserved worker heterogeneity and observable firm- and worker-level factors, but the source of identifying variation remains the same. 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 4 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.

Finally, column 5 includes firm-by-year fixed effects, which absorb all time-varying firm-specific wage policies and shocks. Here, the interaction between young firm status and local job finding rates remains negative and statistically significant, albeit with a smaller magnitude and reduced precision. The identifying variation in this specification comes exclusively from within-firm, within-year differences in the local labor market conditions faced by workers residing in different commuting zones. This constitutes a highly stringent test: even when comparing workers employed by the same firm in the same year, those located in areas with higher job-finding rates receive lower wages if the firm is young. Together, these results underscore the empirical relevance of the mechanism highlighted in the model: when labor market conditions improve, young firms are able to offer lower wages because the value of outside options rises for workers, reducing the compensation they require to accept riskier job matches.

When controlling for both worker and firm fixed effects (column 4), a one standard deviation increase in the job finding rate reduces the young-firm wage premium by 0.65 p.p., which substantially exceeds the baseline premium itself. 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.

We have verified that the results in Table 4 are robust to defining young firms using a five-year threshold (see Appendix B.2) and to clustering standard errors at the worker-firm level instead of commuting zones.

5.3 Experimenting-Firms Wage Premia and Job Finding Rates

5.3.1 Empirical Strategy

We now turn to a more direct test of the mechanism. In the model, the decline in average wages among young firms in response to improved labor market conditions is entirely driven by those engaged in risky experimentation. This insight motivates our second empirical strategy, which exploits variation among young firms to test whether wage differentials between experimenting and non-experimenting firms respond systematically to local job-finding rates. To this end, we construct a measure of risky experimentation at the firm level. Inspired by Castro et al. (2009) and Choi (2017), we develop a volatility-based indicator that captures the idea—consistent with our model—that firms engaged in risky experimentation face more dispersed business outcomes. Importantly, this measure is constructed using the full sample of firms observed in the data, not just young firms. We compute firm-level volatility using all available years of data in which the firm is active, regardless of its age at the time. The sample is restricted to young firms only at the stage of the wage regressions, when testing the mechanism empirically.

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 residual component of sales growth by estimating the following regression:

$$g_{jt} = \alpha_j + \gamma_{kt} + \beta_1 \log(size_{jt}) + \beta_2 \log(age_{jt}) + \epsilon_{jt}, \tag{24}$$

where k indexes the industry to which firm j belongs. The residual $\hat{\epsilon}_{jt}$ captures firm-level deviations in growth that are unexplained by firm size, age, or industry-year conditions, and thus reflects idiosyncratic fluctuations in firm growth. Since experimentation in our model can lead to a wide range of outcomes—including failure and exit as well as the emergence of highly successful or even superstar firms—it generates greater dispersion in sales trajectories over a firm's life relative to safe firms. We seek to capture this dispersion by measuring the volatility of residual sales growth over time. To that end, we square $\hat{\epsilon}_{jt}$ and estimate a time-invariant, firm-level volatility measure while controlling for industry-year-specific volatility, i.e.,

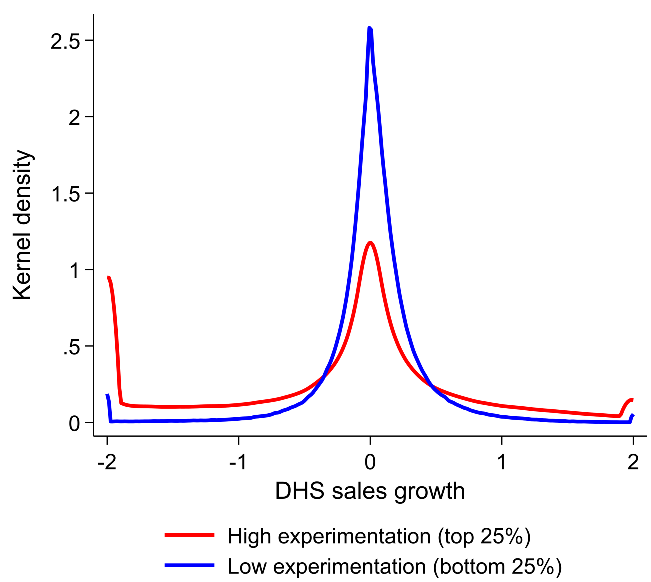
$$\hat{\epsilon}^2_{jt} = \chi_j + \kappa_{kt} + \upsilon_{jt}, \tag{25}$$

where χ_j serves as our proxy for the degree of risky experimentation. The inclusion of industry-year fixed effects, κ_{kt}, ensures that χ_j captures firm-specific volatility relative to the typical volatility observed within the same industry and year, isolating idiosyncratic experimentation intensity from broader volatility differences across industries or over time.

To assess whether our volatility measure χ_j captures the dispersion in outcomes implied by risky experimentation, we examine the distribution of raw DHS sales growth rates g_{jt} across different levels of χ_j. Specifically, we divide firms into quartiles of χ_j within each year and estimate the kernel density of g_{jt} separately for each quartile. This exercise serves as a validation check: because χ_j is constructed as an average squared residual and does not mechanically impose symmetry, i.e. twosided fat tails, a more dispersed distribution of growth rates—featuring both extreme failures and successes—among high-χ_j firms would lend empirical support to its interpretation as a proxy for risky experimentation.

Figure 3 plots the kernel density estimates for firms in the top (red) and bottom (blue) quartiles of χ_j, which we interpret as high- and low-experimentation firms, respectively. Firms in the top quartile exhibit markedly thicker tails: they are more likely to fail, as indicated by the larger mass at the far left, but also more likely to achieve rapid growth, as shown by the higher density in the right tail. This pattern is consistent with our model's prediction that experimentation entails a broader distribution of potential outcomes, encompassing both failure and outsized success. In Appendix B.3, we show that these results are robust to computing the kernel density after residualizing sales growth—either by including industry-year fixed effects or by controlling for the full set of covariates in equation (24).

Figure 3: Distribution of sales growth: high vs. low degree of experimentation (χ_j)



Building on specification (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, older 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:

$$w_{it} = \eta_t + \beta X_{it} + \gamma_1 \hat{\chi}_{J(i,t)} + \gamma_2 f_{M(i,t)} + \delta \hat{\chi}_{J(i,t)} \times f_{M(i,t)} + \epsilon_{it}, \tag{26}$$

where $\hat{\chi}_{J(i,t)}$ denotes the degree of experimentation for firm $j = J(i,t)$ estimated from equation (25). Our main coefficient of interest is δ, which we expect to be negative.

5.3.2 Results

Table 5: Regression results

Experimentation	-0.000503	-0.00171	-0.00374	-0.00528**	0
	(0.00325)	(0.00282)	(0.00254)	(0.00230)	(.)
Job Finding Rate	0.00656***	0.00199	0.00178	0.00224	0.00108
	(0.00201)	(0.00152)	(0.00154)	(0.00144)	(0.00122)
Exp. × Job Finding Rate	-0.00757***	-0.00418***	-0.00446***	-0.00660***	-0.00325*
	(0.00176)	(0.00146)	(0.00156)	(0.00142)	(0.00167)
Observations	719,794	719,794	719,789	719,322	708,808
R-squared	0.901	0.911	0.912	0.916	0.945
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. The degree of experimentation is measured by χ_j in Equation (25). Time-varying worker and firm controls include worker age squared, worker age cubed, worker age interacted with education, worker age squared interacted with education, worker age cubed interacted with education, firm size, firm size squared, firm size cubed, and worker tenure at the firm. Worker age is log-transformed and normalized by 40, while education is measured in years of study and also log-transformed. Firm size is measured as the log of the number of workers, and worker tenure represents the total years of employment at the firm. 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.

Table 5 shows that the point estimates on the experimentation coefficient are consistently negative across specifications, becoming statistically significant only in the most saturated regression. This is consistent with the idea that highly experimental firms—often pursuing ambitious and uncertain projects—may be more financially constrained and therefore more likely to rely on wage deferral. As highlighted by Michelacci and Quadrini (2005), such firms can alleviate capital constraints by compensating workers with lower initial wages in exchange for future gains. This mechanism helps explain the observed negative wage differential, even in the absence of variation in local labor market conditions.

We now turn to the key object of interest. Table 5 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 located 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 intensity 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 10 percent level and maintains a magnitude in the same broad range as previous specifications. This provides robust evidence that experimentation-related 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 0.3 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 lower wages in firms pursuing uncertain but potentially high-return ventures.

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 young and mature firms and between experimenting and non-experimenting firms—decline where job-finding rates are higher. This supports our theoretical prediction that greater labor market security 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:

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

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

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

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

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:

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

A.2 Labor market clearing

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

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

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

In addition, labor market tightness is computed as:

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

where $v^{s,*}(\boldsymbol{z}, n_{-1})$, $v^{ry,*}(\boldsymbol{z}, n_{-1})$, and $v^{rm,*}(\boldsymbol{z}, n_{-1})$ represent the optimal vacancy postings for safe firms, risky 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,

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

B Appendix for empirical analysis

B.1 Summary statistics

Figure 4 presents the relationship between firm age and hourly earnings in Denmark. Consistent with prior research (Babina et al., 2019; Brown and Medoff, 2003; Davis and Haltiwanger, 1991; Dunne and Roberts, 1990), we observe that earnings tend to increase with firm age. This pattern has been widely documented in the literature, where older firms typically offer higher wages due to greater financial stability, accumulated human capital, and better worker-firm matching.

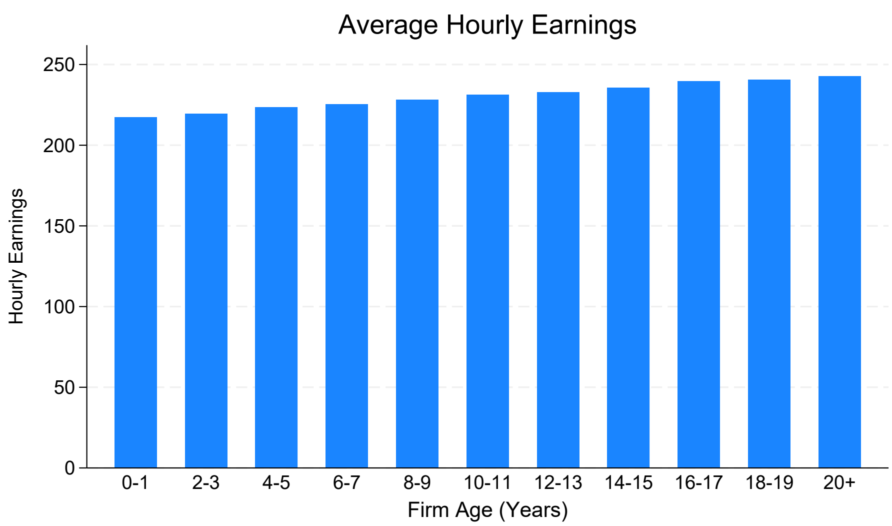
Previous studies, such as Brown and Medoff (2003), suggest that younger firms may face credit constraints, limiting their ability to offer competitive wages. Additionally, Hurst and Pugsley (2011) highlight that young firms often provide nonpecuniary benefits, potentially compensating for lower initial wages. Moreover, as Babina et al. (2019) argues, these wage differentials are also influenced by worker sorting, as younger firms tend to attract individuals with lower observed earning potential.

Our Danish data lend support to these theoretical explanations. The earnings gap between young and mature firms is evident, reinforcing the notion that firm age plays a crucial role in wage determination. As in previous studies (Davis and Haltiwanger, 1991; Dunne and Roberts, 1990), this relationship suggests that both worker selection and firm-specific constraints contribute to observed wage disparities.

The observed wage gap between young and old firms suggests the necessity of controlling for both worker and firm fixed effects in order to retrieve an unbiased estimate of the young-firm pay premium. As emphasized by Babina et al. (2019), without accounting for worker heterogeneity, the estimated pay gap could largely reflect differences in worker ability, preferences, or career trajectories rather than a true firm-age effect. Similarly, firm-specific heterogeneity, such as persistent productivity differences or compensation structures, may confound the relationship between firm age and pay. By incorporating fixed effects at both the worker and firm level, we can come closer to isolating the genuine pay premium (or penalty) associated with young firms from underlying selection mechanisms that drive sorting in the labor market.

However, it is important to emphasize that our primary object of interest is not the wage premium itself—whether between young and mature firms or between experimenting and non-experimenting young firms—but rather the sensitivity of these wage differentials to local labor market conditions, specifically the employment inflow rate. This response is the central mechanism we seek to test.

Figure 4: Hourly earnings



B.2 Robustness

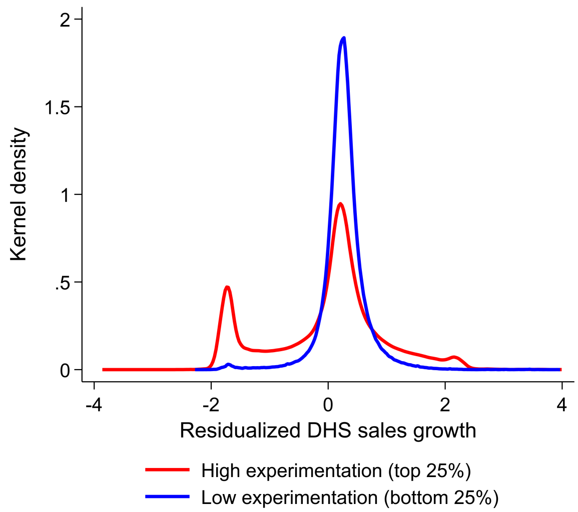
Table 6: Regression results with young firms $\leq$ 5 years

Young	-0.0843***	-0.0238***	0.00423***	0.00357***	0
	(0.00614)	(0.00154)	(0.00140)	(0.000676)	(.)
Job Finding Rate	0.0581***	0.0138***	0.00871***	0.00692***	0.00357***
	(0.0132)	(0.00136)	(0.00138)	(0.00126)	(0.000694)
Young $\times$ Job Finding Rate	-0.0174***	-0.00248**	-0.00487***	-0.00540***	-0.00140*
	(0.00228)	(0.000988)	(0.000751)	(0.000840)	(0.000719)
Observations	16,169,311	15,722,215	15,677,334	15,654,518	15,301,911
R-squared	0.0162	0.831	0.859	0.881	0.907
Worker Controls	No	No	Yes	Yes	Yes
Worker FE	No	Yes	Yes	Yes	Yes
Firm FE	No	No	No	Yes	No
Year FE	Yes	Yes	Yes	Yes	No
Year x Firm FE	No	No	No	No	Yes

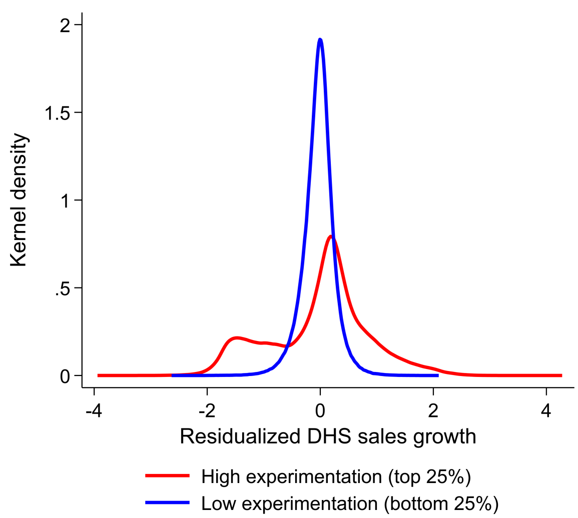
Notes: This table presents the baseline results for the wage premium at young firms and its interaction with labor market conditions. The sample consists of a matched worker-year panel from 2008 to 2023, with the dependent variable being the log of yearly real hourly wages. Young firms are defined as those less than three years old at the start of a given year. Time-varying worker and firm controls include worker age squared, worker age cubed, worker age interacted with education, worker age squared interacted with education, worker age cubed interacted with education, firm size, firm size squared, firm size cubed, and worker tenure at the firm. Worker age is log-transformed and normalized by 40, while education is measured in years of study and also log-transformed. Firm size is measured as the log of the number of workers, and worker tenure represents the total years of employment at the firm. In regressions with worker fixed effects, worker age and education are excluded as linear controls since they are collinear with the fixed effects. Note that the job finding rate is demeaned and divided by the standard deviation, so a unit increase in job finding 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.

B.3 Distribution of sales growth

Figure 5: Dist. of residual sales growth: high vs. low degree of experimentation (χ_j)



(a) After industry-year FE



(b) After full controls