Safety in Unemployment and Risky Experimentation of Young Firms*

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Abstract

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

JEL Codes: E24, J31, J64, J65, L26, O47

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1 Introduction

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

We formalize this mechanism in a model of heterogeneous, multi-worker firms with endogenous experimentation and directed search in the labor market, following Kaas and Kircher (2015). Directed search provides a natural way to characterize the compensating differential. Because workers choose where to search, all hiring firms must offer contracts that deliver the same expected value. Firms whose jobs carry greater separation risk—through layoffs or exit—must therefore pay higher wages to attract workers. A lower cost of unemployment reduces this required compensation, with the largest effect for risky young firms. By lowering their relative labor costs, safer unemployment conditions make experimentation more attractive at entry. Notably, this mechanism does not depend on risk aversion; in a directed-search environment, it arises even when workers are risk neutral.

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

Rather than modeling specific institutions one by one, we interpret this counterfactual as a reduced-form way of capturing policy and institutional forces that affect job finding rate, closely following Engbom (2022).[1] While in reality various institutions operate through distinct channels and may have heterogeneous effects on the economy, we abstract from this complexity. Our objective is not to estimate institution-specific effects but to isolate a common propagation mechanism: how shifts in job finding alter wage differentials between experimenting and non-experimenting firms.

We explore the overall effects of an increase in matching efficiency, which raises the job-finding rate of unemployed workers. The higher job-finding rate lowers the compensating differential that risky young firms must pay to attract workers. The resulting shift in relative wages encourages a greater share of entrants to pursue risky experimentation, further raising aggregate productivity. Overall, productivity rises by approximately 1%. Decomposing this gain into changes in the number of firms, the productivity distribution, and allocative efficiency, we find that it is largely driven by an increase in the share of highly productive firms, as a larger share of entrants choose to undertake risky experimentation.

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

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

persion in ex-post permanent productivity; empirically, we recover each firm's permanent growth type and classify "experimenting" firms as tail types of that distribution, treating the remainder as safe.

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

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

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

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

To isolate the worker-side mechanism more cleanly, we designed a survey experiment that elicits the wage differential workers require to accept employment at a higher-failure-risk young firm, and we experimentally vary unemployment duration. In a short module embedded in Danmarks Nationalbank's nationally-representative Survey of Consumers' Expectations, respondents first report their expected unemployment duration.[2] They are then randomly assigned to a vignette in which this duration is hypothetically *halved* or *doubled*, and they compare two otherwise identical jobs that differ only in firm risk and growth potential: a stable firm with an annual closure rate of about 4% and an experimental young firm with an annual closure rate of about 20%. Respondents state whether they would switch only for higher pay, also at the same pay, or even for lower pay, and then quantify the required reservation premium (or acceptable discount).

Consistent with the theory, experimentally worsening unemployment conditions increases the required wage differential: Regressing the stated risky–safe wage differential on the randomized log change in unemployment duration yields a positive and statistically significant effect; a doubling of expected unemployment duration increases the required wage differential by about 3.6 percentage points. Note that in the calibrated model, the same elasticity can be computed, which implies that a doubling of expected unemployment duration increases the wage differential by 2.0 percentage points. Our estimate of the productivity gain from a higher job-finding rate is thus

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

conservative. This experimental evidence strengthens the causal interpretation of the negative wage-differential–job-finding correlation uncovered in the Danish microdata.

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

Our paper also contributes to the vast literature on the implications of firm heterogeneity for aggregate productivity in the presence of labor market frictions.[3] In settings with firm heterogeneity, differences in aggregate productivity arise from (1) the underlying productivity distribution itself and (2) the allocation of resources across producers, given that distribution (Hsieh and Klenow, 2009). Hopenhayn and Rogerson (1993) show that firing costs reduce aggregate productivity by distorting resource allocation. Bilal et al. (2022) develop a tractable yet rich model of firm and worker dynamics with search and matching frictions and quantify the misallocation costs arising from such frictions. In contrast to this misallocation-focused perspective, our paper emphasizes how labor market institutions influence the productivity

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

distribution itself through the unemployment channel and the endogenous choice of risky experimentation by entrants. Relatedly, Engbom (2022) also show that more fluid labor markets lead to higher aggregate productivity, but through a different mechanism—emphasizing job-to-job transitions and human capital accumulation.

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

2 The model

We build on the influential directed-search framework of Kaas and Kircher (2015), which combines heterogeneous multi-worker firms with a tractable characterization of equilibrium wage setting in frictional labor markets. This structure is especially well suited to our question because it makes compensating differentials across firms transparent: firms that expose workers to different separation risks must adjust wages to attract applicants. We extend the framework by allowing entrants to choose whether to undertake risky experimentation, a decision that changes both their subsequent productivity process and the separation risk borne by their workers. In what follows, we describe the environment and labor-market structure, characterize firm and worker value functions, and derive the wage rule implied by directed search. 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

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

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

Because entrants are ex ante identical, all firms would choose the same business model absent additional heterogeneity. To generate dispersion in entry choices and allow safe and experimenting firms to coexist in equilibrium, we introduce idiosyncratic taste shocks for the safe business model, in the spirit of Hurst and Pugsley (2011). These shocks capture nonpecuniary motives for choosing the safe option and imply that some firms do so even when experimentation has a higher expected pecuniary payoff.

Firms face decreasing returns to scale and use labor as the only factor of production. The labor market is frictional, so firms must post vacancies to hire workers. There is a unit measure of identical workers, who can be either employed or unemployed. Only unemployed workers search. Unemployed workers receive benefits b, while employed workers are paid the wage specified in the posted contract. There are no aggregate shocks.

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

- **Safe firms (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 (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 (rm)** are those that previously chose risky experimentation and have since drawn their permanent productivity. These firms operate with the realized value going forward.

2.2 The frictional labor market with directed search

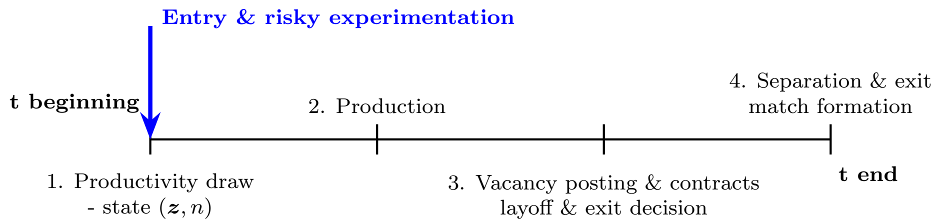
Firms compete for workers by posting long-term contracts. A contract specifies the wage paid to the worker and the separation and exit probabilities associated with the match in future states. Unemployed workers observe posted contracts and direct their search toward the offer that delivers the highest value. If a firm wants to fill a vacancy with probability m, it must attract $\lambda(m)$ workers per vacancy, where $\lambda(m) = \left(\frac{m^{-r}-1}{k}\right)^{-1/r}$ is the CES matching technology of Kaas and Kircher (2015). The function $\lambda(m)$ is increasing in m: filling vacancies faster requires attracting a longer queue of applicants per vacancy. Conditional on searching in that submarket, a worker's matching probability is $m/\lambda(m)$. If the firm exits before the match becomes productive, however, the worker remains unemployed; hence the probability of starting employment at that firm next period is $(1-\delta)m/\lambda(m)$.

2.3 Timing

The timing within each period is as follows and is depicted in Figure 1. At the beginning of period t, the state of each incumbent firm is given by its type, productivity, age, and inherited workforce n. New firms enter with zero workers, permanent productivity z_e, and temporary productivity equal to the mean of the ergodic distribution of the temporary productivity process. Entrants then draw a taste shock and choose whether to operate the safe business model or undertake risky experimentation.

Next, young firms—incumbents from earlier periods that still operate with the entry-level productivity z_e—draw a new permanent productivity level with probability φ and thereby transition into mature firms, while mature firms retain their permanent productivity from the previous period. All firms draw a persistent tem-

Figure 1: Timing



porary productivity shock. We denote productivity by $\boldsymbol{z} = (z_p, z_i)$, where z_p is the permanent component and z_i is the temporary component.

Firms then produce using their inherited workforce n and pay the fixed operating cost ψ_o. They choose vacancy postings, the contracts offered to new hires, layoffs, and whether to exit at the end of the period. The exogenous worker quit rate is s_0, and firms may also lay off workers at no cost, so the total separation rate satisfies $s \geq s_0$. If the optimal choice is to downsize, firms post no vacancies. The exogenous exit rate is δ_0, but firms may also exit endogenously due to the fixed operating cost, so the total firm exit rate satisfies $\delta \geq \delta_0$.

At the end of the period, firms' separation and exit decisions are implemented and search outcomes are realized. Only workers who were unemployed at the beginning of the period search during period t; workers separated from incumbent jobs, including those displaced by firm exit, enter unemployment in period $t+1$ and search from then on. Matches formed in period t also become productive only in period $t+1$, and only if the firm survives to the next period.

2.4 Workers

Workers have linear utility. A worker who enters the period unemployed receives unemployment benefits b during the period and searches over posted contracts. Unemployed workers direct their search toward the contract that delivers the highest expected value.

The value of unemployment, denoted by U, is

$$U = b + \max_{\mathcal{C}_\iota} \beta \left(\frac{m_\iota}{\lambda(m_\iota)} (1 - \delta_\iota) \, \mathbb{E}_{z_\iota} E^j(\boldsymbol{z}', n'; \mathcal{C}_\iota) + \left(1 - \frac{m_\iota}{\lambda(m_\iota)} (1 - \delta_\iota) \right) U' \right), \quad (1)$$

where $\beta \in (0,1)$ is the discount factor, $\mathcal{C}_\iota$ is the contract offered by firm ι, and $\lambda(m_\iota)$ is the associated queue length. The function $E^j(\boldsymbol{z}, n; \mathcal{C}_\iota)$ denotes the value of employment under contract $\mathcal{C}_\iota$ when this contract is offered by a firm of type $j \in \{s, ry, rm\}$ with productivity $\boldsymbol{z}$ and n workers. The operator $\mathbb{E}_{\boldsymbol{z}_\iota}$ denotes the expectation, conditional on firm ι surviving to the next period, over the future productivity uncertainty relevant for firm ι. For safe firms and risky mature firms, this is the temporary productivity draw. For risky young firms, it also includes the maturity transition and, conditional on maturity, the draw of permanent productivity. Conditional on the current state and the firm's current policy choices, the next-period workforce n' is determined and enters the employment value as an argument. The value $E^j(\boldsymbol{z}', n'; \mathcal{C}_\iota)$ is then evaluated under the contract $\mathcal{C}_\iota$. Finally, δ_ι is the current-period exit probability specified in $\mathcal{C}_\iota$. The value of unemployment thus consists of the flow benefit b plus the discounted continuation value: with probability $\frac{m_\iota}{\lambda(m_\iota)}(1-\delta_\iota)$ the worker matches with a surviving firm and obtains the expected employment value $\mathbb{E}_{z_\iota} E^j(\boldsymbol{z}', n'; \mathcal{C}_\iota)$; otherwise she remains unemployed with continuation value U'.

Since there are no aggregate shocks, $U' = U$. Rearranging (1) then yields

$$(1-\beta)U = b + \underbrace{\max_{\mathcal{C}_\iota} \beta \left(\frac{m_\iota}{\lambda(m_\iota)}(1-\delta_\iota) \left[\mathbb{E}_{z_\iota} E^j(\boldsymbol{z}', n'; \mathcal{C}_\iota) - U \right] \right)}_{:=\rho}. \tag{2}$$

Intuitively, because unemployed workers can direct their search, equilibrium contracts that attract workers must deliver the same search value. Otherwise, workers would direct their search toward any contract that is marginally better, and firms offering the inferior contract would fail to hire. Thus, if a contract offers a higher employment value to workers—that is, a higher $\mathbb{E}_{z_\iota} E^j(\boldsymbol{z}', n'; \mathcal{C}_\iota)$—more workers queue for it, which increases the queue length and lowers the worker's matching probability.

The value of employment $E^j(\boldsymbol{z}, n; \mathcal{C}_\iota)$ under contract $\mathcal{C}_\iota$ is

$$E^j(\boldsymbol{z}, n; \mathcal{C}_\iota) = w_\iota + \beta \left(p_{\varsigma_\iota} \mathbb{E}_{z_\iota} E^j(\boldsymbol{z}', n'; \mathcal{C}_\iota) + (1 - p_{\varsigma_\iota}) U' \right), \tag{3}$$

where $p_{\varsigma_\iota} = (1-s_\iota)(1-\delta_\iota)$ is the probability that the match survives to the next period. The separation probability s_ι and exit probability δ_ι, and hence p_{ς_ι}, are allowed to be state contingent.

To derive an expression for the flow wage w_ι, we assume that firms offer a flat-wage contract: as long as a worker remains with the firm, she is paid a constant wage. Under this assumption, iterating the employment value (3) forward yields

$$E^j(\boldsymbol{z}, n; \mathcal{C}_\iota) - U = A_\iota(\boldsymbol{z}, n) \left(w_\iota - (1-\beta)U \right), \tag{4}$$

where $A_\iota(\boldsymbol{z}, n)$ is defined recursively by $A_\iota(\boldsymbol{z}, n) = 1 + \beta p_{\varsigma_\iota}(\boldsymbol{z}, n) \mathbb{E}_{z_\iota} A_\iota(\boldsymbol{z}', n')$. Thus,

$A_\iota(\boldsymbol{z}, n)$ is the expected discounted duration of the match under contract $\mathcal{C}_\iota$. A higher A_ι means that the match is expected to last longer.

Substituting (4) into (2), we obtain the flow wage

$$w_\iota = b + \rho + \frac{1}{\beta(1-\delta_\iota)} \frac{\lambda(m_\iota)}{m_\iota} \frac{\rho}{\mathbb{E}_{z_\iota} A'_\iota}. \tag{5}$$

This expression has a simple interpretation. First, the firm must compensate the worker for the flow value of unemployment, $b+\rho$. Second, a firm that wishes to fill its vacancies faster must offer a higher wage to attract a longer queue, $\lambda(m_\iota)$. Third, the shorter the expected discounted duration of the match, $\mathbb{E}_{z_\iota} A'_\iota$, the higher the wage required to compensate the worker. Thus, all else equal, a riskier firm—one more likely to lay off workers or exit—must pay a wage premium to attract workers.

2.5 Firms

2.5.1 Value functions

Firms hire workers through long-term contracts with commitment. A contract $\mathcal{C}_\tau$ offered to cohort τ specifies state-contingent wages and state-contingent worker-separation probabilities for that cohort. Because firm exit is a firm-level event that separates all workers, we also allow contracts to place state-contingent upper bounds on the firm's exit probability. The current exit probability δ remains a firm-level policy choice, common to all cohorts, but it must respect these outstanding commitments. In principle, this makes each previous hiring cohort and the contract under which it was hired relevant state variables. In the directed-search environment of Kaas and Kircher (2015), however, the allocation can be characterized without solving this high-dimensional decentralized problem directly: past wage promises are payoff-relevant transfers in the decentralized economy, while hiring, separation, and exit policies can be recovered from the corresponding planner allocation. This property keeps the state space tractable. We nevertheless first write the firm's problem in its most general form.

For a firm of age a and type $j \in \{s, ry, rm\}$, let $V_a^j\left[\{\mathcal{C}_\tau\}_{\tau=0}^{a-1}, \{n_\tau\}_{\tau=0}^{a-1}, (z_p, z_i)\right]$ denote the value at the beginning of the period. The firm has productivity $\boldsymbol{z} = (z_p, z_i)$ and a workforce n composed of previous hiring cohorts $\{n_\tau\}_{\tau=0}^{a-1}$, each associated with a contract $\mathcal{C}_\tau$. Safe and risky mature firms solve the same optimization problem conditional on their current state, since both operate with known permanent productivity.

For safe firms, this permanent productivity is fixed at z_e; for risky mature firms, it is the realized draw z_m from prior experimentation. Accordingly, the same value-function expression applies to both types, with $z_p = z_e$ for safe firms and $z_p = z_m$ for risky mature firms.

For firms that are safe or risky-mature ($j \in \{s, rm\}$), the value function is

$$\begin{aligned} V_a^j \left[\{\mathcal{C}_\tau\}_{\tau=0}^{a-1}, \{n_\tau\}_{\tau=0}^{a-1}, (z_p, z_i)\right] = \max_{\delta, m, v, \mathcal{C}_a} F((z_p, z_i), n) - W - c(v, n) - \psi_o \\ + \beta(1-\delta)\, \mathbb{E}_{z_i'|z_i} V_{a+1}^j \left[\{\mathcal{C}_\tau\}_{\tau=0}^{a}, \{n_{\tau+}\}_{\tau=0}^{a}, (z_p, z_i')\right], \end{aligned} \tag{6}$$

subject to

$$n_{a+} = mv, \quad n_{\tau+} = (1 - s_\tau(z_p, z_i))\, n_\tau, \quad \delta \in [\delta_0, \min_{0 \le \tau \le a-1} \delta_\tau(z_p, z_i)], \quad s_\tau(z_p, z_i) \ge s_0,$$

$$W = \sum_{\tau=0}^{a-1} w_\tau n_\tau, \quad n = \sum_{\tau=0}^{a-1} n_\tau,$$

$$\rho = \beta \left(\frac{m}{\lambda(m)} (1-\delta) \left(\mathbb{E}_{z_i'|z_i} E^j((z_p, z_i'), n'; \mathcal{C}_a) - U \right) \right) \ \textbf{if} \ m > 0.$$

The function $F((z_p, z_i), n)$ denotes output given the firm's productivity and workforce. The term $c(v, n)$ captures the cost of creating v vacancies when the firm starts the period with n workers. The parameter $\psi_o > 0$ is a fixed operating cost. Finally, $\mathbb{E}_{z_i'|z_i}$ denotes the expectation over next period's temporary productivity, conditional on the current draw z_i.

The constraints have the following interpretation. The update $n_{\tau+}$ captures the workers from cohort τ who remain with the firm next period, conditional on firm survival: workers are separated at the state-contingent rate $s_\tau(z_p, z_i)$ specified in their original contract, with $s_\tau(z_p, z_i) \ge s_0$. The firm may also exit endogenously. Because exit is a firm-level event that separates all cohorts, the chosen exit probability δ must respect the outstanding exit commitments made to previous cohorts and is bounded below by the exogenous exit rate δ_0. The final condition is the worker-attraction constraint for new hires: if the firm wants to hire at vacancy-filling rate m, the contract $\mathcal{C}_a$ must deliver the search premium ρ defined in equation (2).

For *risky young firms*, the expression differs from the previous cases because the firm may mature with probability φ. The continuation value therefore takes expectations over both the maturity transition and, conditional on maturity, the draw of permanent productivity:

$$V_a^{ry}\left[\{\mathcal{C}_\tau\}_{\tau=0}^{a-1},\{n_\tau\}_{\tau=0}^{a-1},(z_p,z_i)\right]=\max_{\delta,m,v,\mathcal{C}_a} F((z_p,z_i),n)-W-c(v,n)-\psi_o$$

$$+\beta(1-\delta)\,\mathbb{E}_{z_i'|z_i}\left[(1-\varphi)V_{a+1}^{ry}\left[\{\mathcal{C}_\tau\}_{\tau=0}^{a},\{n_{\tau+}\}_{\tau=0}^{a},(z_p,z_i')\right]\right.$$

$$\left.+\varphi\mathbb{E}_{z_m}V_{a+1}^{rm}\left[\{\mathcal{C}_\tau\}_{\tau=0}^{a},\{n_{\tau+}\}_{\tau=0}^{a},(z_m,z_i')\right]\right], \tag{7}$$

subject to

$$n_{a+}=mv,\quad n_{\tau+}=(1-s_\tau(z_p,z_i))\,n_\tau,\quad \delta\in[\delta_0,\min_{0\le\tau\le a-1}\delta_\tau(z_p,z_i)],\quad s_\tau(z_p,z_i)\ge s_0,$$

$$W=\sum_{\tau=0}^{a-1}w_\tau n_\tau,\quad n=\sum_{\tau=0}^{a-1}n_\tau,$$

$$\rho=\beta\frac{m}{\lambda(m)}(1-\delta)\left[\mathbb{E}_{z_i'|z_i}\left\{(1-\varphi)E^{ry}((z_p,z_i'),n';\mathcal{C}_a)\right.\right.$$

$$\left.\left.+\varphi\mathbb{E}_{z_m}E^{rm}((z_m,z_i'),n';\mathcal{C}_a)\right\}-U\right]\quad \text{if } m>0.$$

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

2.5.2 Endogenous experimentation and entry

New entrants choose between two business models. We interpret experimentation in the broad sense of Hurst and Pugsley (2011): it is not restricted to high-tech innovation or formal R&D, but instead refers to pursuing a business idea whose market potential is uncertain relative to a more standard activity. A safe entrant replicates an existing business model with relatively predictable outcomes. A risky entrant experiments with a less proven strategy, which exposes the firm to greater downside risk but also creates the possibility of substantially better outcomes. Because entrants are otherwise identical, we introduce idiosyncratic taste shocks, denoted by ϵ, associated with choosing the safe option. These shocks capture nonpecuniary motives for running a business, in the spirit of Hurst and Pugsley (2011).

Let $\mathcal{E}^s\equiv V_0^s(\emptyset,\emptyset,(z_e,\mu_{z_i}))$ and $\mathcal{E}^{ry}\equiv V_0^{ry}(\emptyset,\emptyset,(z_e,\mu_{z_i}))$ denote the values at entry for firms choosing the safe and risky business models, respectively. $\emptyset$ (the empty set) reflects the fact that new entrants have no workers and therefore no prior long-term contracts to honor. Entrants begin with zero workers 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:

$$\mathcal{E}=\mathbb{E}_\epsilon\left[\max\left(\mathcal{E}^s+\epsilon,\mathcal{E}^{ry}\right)\right], \tag{8}$$

where $\mathbb{E}_\epsilon$ 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:

$$\mathcal{E} = \sigma_\sigma \log \left(\exp\left(\frac{\mathcal{E}^s}{\sigma_\sigma}\right) + \exp\left(\frac{\mathcal{E}^{ry}}{\sigma_\sigma}\right) \right), \tag{9}$$

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

$$P(R) = \frac{\exp\left(\frac{\mathcal{E}^{ry} - \mathcal{E}^s}{\sigma_\sigma}\right)}{1 + \exp\left(\frac{\mathcal{E}^{ry} - \mathcal{E}^s}{\sigma_\sigma}\right)}, \tag{10}$$

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

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

2.6 Discussion: The unemployment safety channel

This section highlights the model's core propagation mechanism: a change in the workers' matching rate induced by labor-market institutions alters the wage premium offered by risky young firms compared with safer firms. This wage differential, in turn, shape firms' incentives to engage in risky experimentation.

Recall the wage equation (5):

$$w_\iota = b + \rho + \frac{1}{\beta(1-\delta_\iota)} \frac{\lambda(m_\iota)}{m_\iota} \frac{\rho}{\mathbb{E}_{\boldsymbol{z_\iota}} A'_\iota}.$$

To isolate the channel related to match riskiness, we assume for now that the vacancy creation cost is linear; we relax this assumption in the quantitative analysis. With a linear vacancy creation cost, all firms choose the same vacancy-filling rate, so the worker's matching probability $m/\lambda(m)$ is equalized across firm types. We can therefore compare how a change in this matching probability affects the wage differential between risky and safe young firms. This differential is

$$w_{ry} - w_s = \frac{\rho}{\beta} \frac{\lambda(m)}{m} \left(\frac{1}{(1-\delta_{ry})\mathbb{E}_{\boldsymbol{z_{ry}}} A'_{ry}} - \frac{1}{(1-\delta_s)\mathbb{E}_{\boldsymbol{z_s}} A'_s} \right). \tag{11}$$

First, because expected match duration is shorter at risky young firms than at safe young firms, $(1-\delta_{ry})\mathbb{E}_{\boldsymbol{z_{ry}}} A'_{ry} < (1-\delta_s)\mathbb{E}_{\boldsymbol{z_s}} A'_s$, and hence $w_{ry} > w_s$. In other words, risky young firms must pay a premium to compensate workers for the shorter expected match. More importantly, to see how this premium responds to job-finding conditions, we differentiate $w_{ry} - w_s$ with respect to $m/\lambda(m)$:

$$\frac{\partial(w_{ry} - w_s)}{\partial(m/\lambda(m))} = -\frac{\rho}{\beta}\left(\frac{1}{(1-\delta_{ry})\mathbb{E}_{\boldsymbol{z_{ry}}} A'_{ry}} - \frac{1}{(1-\delta_s)\mathbb{E}_{\boldsymbol{z_s}} A'_s}\right)\left(\frac{\lambda(m)}{m}\right)^2 < 0.$$

Thus a higher worker matching rate reduces the wage premium that risky young firms must pay. Because risky young firms now pay relatively less than safe young firms, the value of choosing the risky path rises relative to the safe path, which increases the share of entrants that undertake risky experimentation.

3 Mapping the model to data

Computation The decentralized equilibrium is analytically intractable because one would need to track the cohort-specific contracts offered to previous hiring cohorts, which greatly expands the state space. Importantly, Kaas and Kircher (2015) show that in this class of directed-search environments the decentralized equilibrium is efficient. The allocation can therefore be computed from the Bellman equation for the social value of a firm, together with the free-entry condition. We solve the model using this social-value representation, described in Appendix A.3.

Functional forms We assume a standard decreasing returns-to-scale technology, $F((z_p, z_i), n) = z_p z_i n^{\alpha}$, with $\alpha < 1$. Experimenting firms draw permanent productivity upon maturity from a Pareto distribution with shape parameter ξ and lower bound x_m. The persistent temporary productivity z_i follows an AR(1) process, $\log(z_i') = \rho_z \log(z_i) + \epsilon_z$, with $\epsilon_z \sim N(0, \sigma_z^2)$. The vacancy cost function is $c(v, n) = \frac{\chi_0}{1+\chi_1}\left(\frac{v}{n}\right)^{\chi_1} v$.

Calibration strategy We divide the model parameters into two groups: those set externally before the moment-matching procedure and those calibrated internally to match informative moments. The model is calibrated to the Danish economy, with one period corresponding to a quarter. Wherever possible, we use data from the Danish National Accounts or microdata from Danish administrative registers. We rely on estimates from other economies only when comparable Danish evidence is unavailable. Table 1 reports the calibrated parameter values and their target moments.

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, following the structural labor-demand estimates of Cooper et al. (2004). Given the CES matching function $\lambda(m) = \left(\frac{m^{-r}-1}{k}\right)^{-1/r}$, the parameters r and k can be recovered from a target queue length $\bar{\lambda}$, a target job-finding rate f, and the elasticity ϵ of the job-finding rate with respect to the vacancy-to-unemployment ratio: $r = \log(\epsilon)/\log(\bar{\lambda}f)$ and $k = (1-\epsilon)/f^r$. Following Petrongolo and Pissarides (2001), we set $\epsilon = 0.5$, and we target a quarterly job-finding rate of $f = 0.48$ for Denmark (Darougheh et al., 2024). Because we target an average queue length $\bar{\lambda} = 1$ below, r is set to 0.944 and k to 1. We set the quarterly probability φ that a young firm transitions to maturity to 1/12, consistent with the three-year definition of young firms used in the empirical analysis. The persistence of the temporary productivity process is set to 0.659, following Khan and Thomas (2013). Finally, the curvature parameter χ_1 in the vacancy-cost function is set to 2 (Kaas and Kircher, 2015).

Internally calibrated parameters The remaining parameters are set to match informative moments from the data. Unless otherwise noted, we compute moments using employer–employee data from Statistics Denmark, aggregated to the firm level. 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 the dispersion of DHS employment growth (Davis et al., 1998). The scale parameter χ_0 of the vacancy cost function is calibrated to match an average queue length of $\bar{\lambda} = 1$, where $\bar{\lambda}$ is the ratio of the vacancy-filling rate to the worker's matching probability.

The exogenous exit probability δ_0 and the operating cost ψ_o are jointly calibrated to match annualized exit hazard rates at ages 3 and 10. The average sizes of young firms, defined as firms less than three years old, and mature firms, defined as firms more than three years old, identify the productivity of new entrants, z_e, and the lower bound of the Pareto distribution, x_m. The worker's exogenous separation rate, s_0, is set to match the unemployment rate. The unemployment benefit b is calibrated to match the observed ratio of unemployment to employment income in Denmark (Darougheh et al., 2024). Finally, the entry cost ψ_e is chosen to satisfy the free-entry condition in the baseline equilibrium. Since the overall scale of the model is normalized by the baseline search premium ρ, this pins down ψ_e without affecting the model's comparative statics.

The parameter σ_σ warrants special attention because it governs how changes in relative entry values translate into changes in the equilibrium composition of entrants. This margin is central to our mechanism. Labor-market institutions affect the wage premia required by workers at risky firms; these wage premia, in turn, change the value of choosing the risky business model relative to the safe one. The parameter σ_σ determines how strongly this change in relative value shifts the share of entrants that experiment, and therefore how strongly the mechanism reshapes the firm-productivity distribution.

Recall that the share of entrants choosing risky experimentation is

$$P(R) = \frac{\exp\left((\mathcal{E}^{ry} - \mathcal{E}^s)/\sigma_\sigma\right)}{1 + \exp\left((\mathcal{E}^{ry} - \mathcal{E}^s)/\sigma_\sigma\right)}.$$

Let $\Delta\mathcal{E} \equiv \mathcal{E}^{ry} - \mathcal{E}^s$. The sensitivity of experimentation to the relative entry value is

$$\frac{\partial P(R)}{\partial \Delta\mathcal{E}} = \frac{1}{\sigma_\sigma} P(R)\big(1 - P(R)\big).$$

Thus, for a given baseline share of experimenting entrants, a smaller σ_σ implies that entrants respond more strongly to changes in the pecuniary return to experimentation. Conversely, as $\sigma_\sigma \to \infty$, the preference shock dominates the pecuniary value difference $\mathcal{E}^{ry} - \mathcal{E}^s$, so $P(R) \to 1/2$ and changes in relative entry values have vanishing effects on the experimentation share. In this limit, institutions that alter wage premia have little effect on the firm-productivity distribution through the entry-composition margin.

In the baseline, we target a risky share of $P(R) = 0.6$. This target is motivated by Hurst and Pugsley (2011), who document that roughly one-third to one-half of entrepreneurs report no intention to introduce new products or services. We interpret these firms as the empirical counterpart of safe businesses in the model, so that the implied share of entrants pursuing experimentation is around one-half to two-thirds. Given the target $P(R) = 0.6$ and the model-implied value of $\mathcal{E}^{ry} - \mathcal{E}^s$, σ_σ is recovered as

$$\sigma_\sigma = \frac{\mathcal{E}^{ry} - \mathcal{E}^s}{\log(P(R)/(1 - P(R)))}.$$

Intuitively, if the pecuniary value of experimentation, $\mathcal{E}^{ry} - \mathcal{E}^s$, is large, greater dispersion in taste shocks is needed to keep the experimentation share fixed at the 0.6 target.

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)		
k	Matching efficiency	1.00	Darougheh et al. (2024)		
r	Matching elasticity	0.944	Petrongolo and Pissarides (2001)		
φ	Prob. of being mature	1/12	3 years duration as young firms		
ρ_z	Persistence of temp. prod.	0.659	Khan and Thomas (2013)		
χ_1	Vacancy fn curv. param.	2.00	Kaas and Kircher (2015)		
			B. Internally calibrated		
ξ	Shape of perm. prod. dist.	2.024	Emp. share of top 1%	0.404	0.561
σ_z	SD of temp. prod. shocks	0.279	SD of log emp growth	0.172	0.323
χ_0	Vacancy cost scale	0.009	average queue	0.889	1.000
δ_0	Exogenous exit rate	0.035	Exit hazard (age 10)	0.136	0.108
ψ_o	Operating cost	0.002	Exit hazard (age 3)	0.171	0.165
z_e	Entrants' productivity	0.013	Average size of young firms	8.607	9.499
x_m	Pareto lower bound	0.004	Average size of old firms	24.00	21.66
s_0	Worker separation rate	0.001	Unemployment rate	0.061	0.055
b	Replacement ratio	0.001	Darougheh et al. (2024)	0.307	0.300
σ_σ	Scale of safe taste shocks	0.020	Hurst and Pugsley (2011)	0.600	0.600
ψ_e	Entry cost	0.613	Normalization		

4 Model experiments

In this section, we study the effects of higher matching efficiency, which raises workers' equilibrium job-finding rate. Following Engbom (2022), we use this counterfactual as a reduced-form way to capture institutions that hinder labor-market flows, such as employment protection, business regulations, and labor taxes (Hopenhayn and Rogerson, 1993; Pries and Rogerson, 2005). This strategy is in the spirit of the indirect approach in the misallocation literature, where institutional frictions are represented as wedges in order to isolate common aggregate mechanisms without modeling each institution separately (Hsieh and Klenow, 2009). Our goal is not to identify the effect of any specific institution, and we abstract from the distinct channels through which particular policies operate. Instead, we isolate a common propagation mechanism: institutions that affect job-finding conditions change the wage differentials between experimenting and non-experimenting firms, thereby altering the incentive to experiment.

Specifically, we analyze how the stationary equilibrium of the calibrated economy responds to an increase in matching efficiency, implemented by lowering k. For a given vacancy-filling probability m, a lower k reduces the queue length $\lambda(m)$ and

Table 2: Higher Job Finding Rate and Wages, Experimentation, and Young Firms

	Baseline	Low k	Δ
Job Finding Rate	0.44	0.56	12.30
Entrants Wage (Safe)	3.53×10^{-3}	3.54×10^{-3}	0.14
Entrants Wage (Risky)	3.80×10^{-3}	3.78×10^{-3}	-0.58
Young Firm Wage	3.35×10^{-3}	3.38×10^{-3}	0.96
Mature Firm Wage	3.24×10^{-3}	3.29×10^{-3}	1.57
Share of Experimentation	0.60	0.66	6.42
Entrants Mass	2.11×10^{-3}	2.12×10^{-3}	0.81
Young Firm Share	0.36	0.37	0.78
Young Firm Employment Share	0.17	0.17	0.27

Notes: This table shows how a higher job finding rate, driven by higher matching efficiency (lower k), affects wage setting, experimentation, and young firm shares. The parameter k is reduced by 25% from 1 to 0.75. The column "Low k" reports results for $k = 0.75$, and the column Δ shows the difference between "Low k" and the baseline. The unit of Δ is percentage change for entrants mass, entrants wages (safe and risky), young firm wage, and mature firm wage. For the job finding rate, share of experimentation, young firm share, and young firm employment share, the unit is percentage point (p.p.) change.

therefore raises the worker's matching probability $m/\lambda(m)$. In equilibrium, this improves workers' job-finding conditions. Importantly, the change in matching technology affects firms only through the wage they must offer to attract workers: in the firm's problem—equations (6) and (7)—the matching technology enters only through the worker-attraction constraint. We therefore view the counterfactual of lowering k as a clean way to isolate the mechanism linking job-finding conditions to wages, experimentation, and aggregate productivity.

Table 2 reports how an increase in the job-finding rate, driven by a 25% reduction in k, affects wages, experimentation, and the composition of firms. The overall effects of the policy are shown in the column "Low k". First, the 25% reduction in k raises the average job-finding rate by 12.3 percentage points. Because risky entrants have much shorter expected match durations, the wages they offer fall by 0.58% when job-finding conditions improve, declining relative to safe entrants' wages, which rise slightly by 0.14%. Average wages at young firms rise by approximately 1.0%, while wages at mature firms rise by more, about 1.6%. Since experimentation occurs while firms are young, expected match durations are shorter at young firms, which dampens their wage response. The decline in risky entrants' relative wages raises the share of entrants choosing to experiment by roughly 6 percentage points, which in turn raises overall firm entry. Greater experimentation also raises the failure rate as young firms transition to maturity, increasing 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.

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

$$TFP = \underbrace{M^{1-\alpha}}_{\text{Total mass}} \times \underbrace{\left(\frac{1}{M^{1-\alpha}} \left(\int z_k^{\frac{1}{1-\alpha}} dk \right)^{1-\alpha} \right)}_{\text{Productivity distribution}}$$
$$\times \underbrace{\left(\frac{1}{\left(\int z_k^{\frac{1}{1-\alpha}} dk \right)^{1-\alpha}} \left(\frac{\int z_k^{\frac{1}{1-\alpha}} (n_k/y_k)^{\frac{\alpha}{1-\alpha}} dk}{\left(\int z_k^{\frac{1}{1-\alpha}} (n_k/y_k)^{\frac{1}{1-\alpha}} dk \right)^{\alpha}} \right) \right)}_{\text{Allocative efficiency}}, \tag{12}$$

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

The first term, *total mass*, captures the idea that an increase in the number of firms—holding aggregate employment constant—lowers the scale at which each firm operates. Due to decreasing returns to scale, this raises aggregate productivity. The second term, *productivity distribution*, reflects the composition of firms in equilibrium: a larger share of high-productivity firms contributes positively to aggregate productivity. The final term, *allocative efficiency*, measures the degree of labor misallocation, proxied by the dispersion in the marginal product of labor. Greater dispersion indicates poorer allocation, reducing aggregate output for a given level of employment (Hsieh and Klenow, 2009).

Table 3 presents the impact of higher matching efficiency on aggregate productivity and its decomposition. When matching efficiency improves (column "Low k"), aggregate productivity rises by nearly 1.1%. 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 1.2%. This effect is partially offset by a 0.5% decline from the total-mass component. Greater experimentation leads more firms to exit, reducing the number of operating firms. With decreasing returns to scale, fewer firms means that the remaining firms operate

Table 3: TFP Decomposition: Baseline vs. Higher Job Finding Rate

	Baseline	Low k	Δ
Aggregate Productivity (Y/N^{α})	5.51×10^{-3}	5.57×10^{-3}	1.05
Total Mass	0.34	0.34	-0.49
Productivity Distribution	1.91×10^{-2}	1.93×10^{-2}	1.18
Allocative Efficiency	0.84	0.85	0.37

Notes: This table shows how a higher job finding rate, driven by higher matching efficiency (lower k), aggregate productivity and its decomposition. The parameter k is reduced by 25% from 1 to 0.75. The column "Low k" reports results for $k = 0.75$, and the column Δ shows the difference between "Low k" and the baseline. The unit of Δ is percentage change.

at a larger scale, which lowers productivity for a given level of aggregate employment. Finally, allocative efficiency rises by about 0.4%. The reason is that higher matching efficiency lowers the relative wage cost of filling vacancies quickly. This allows firms with stronger incentives to expand to hire more easily, reducing the dispersion in marginal products across firms.

A Testable Implication The model experiment above shows that an increase in the job-finding rate, driven by higher matching efficiency, raises the incentive for firms to engage in risky experimentation, ultimately leading to higher long-run productivity. These effects are driven by the differential wage responses that emerge from directed search: when the job-finding rate is higher, risky young firms are able to pay a lower wage premium than safe young firms. This mechanism yields the following testable implication: among young firms, higher job-finding rates should be associated with lower wages at experimenting firms relative to non-experimenting ones. We test this implication in the next section using geographic 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 across commuting zones, we examine whether, among young firms, wages are lower in experimenting firms relative to non-experimenting ones when job-finding rates are higher.

To map the model to the data, we interpret each commuting zone as a separate local labor market. Directed search should be understood as operating within this local market: workers direct their search across the contracts available in their commuting zone, including contracts offered by experimenting and non-experimenting young firms. Firms in the data may be active in multiple local labor markets, for example through establishments located in different commuting zones. Thus, a single firm can employ workers whose relevant outside options are shaped by different local job-finding conditions. Cross-area differences in job-finding conditions are captured in the model by persistent differences in matching efficiency. We view matching efficiency as a reduced-form parameter that summarizes local forces making it easier or harder for unemployed workers to find jobs. In the model, these differences affect wage setting through the worker-attraction constraint: when local job-finding conditions are better, unemployment is less costly for workers, and the compensating wage premium required by firms with higher separation risk falls. This is the mechanism we take to the data by relating job-finding rates in workers' commuting zones to wage differentials between experimenting and non-experimenting young firms.

5.1 Data

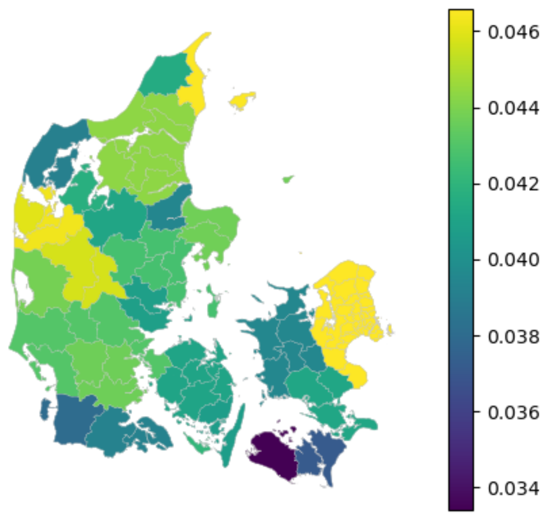
Our analysis uses the following administrative records from Statistics Denmark:

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.

Figure 2: Job finding rate by commuting zone



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

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

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

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

5.2 Experimenting-firms wage premia and job finding rates

5.2.1 Empirical strategy

To test the key mechanism, we construct a model-consistent measure of risky experimentation at the firm level. In the model, firms engaged in risky experimentation draw their permanent productivity from a Pareto distribution, which generates more dispersed business outcomes than those of safe entrants. Guided by this mapping between experimentation and dispersion in permanent outcomes, we classify a firm as experimenting when the *permanent* component of its sales growth lies in the industry–cohort tail, either highly positive or highly negative; the remainder are labeled safe. The classification uses all available observations over the firm's observed life cycle, rather than only outcomes while the firm is young.

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

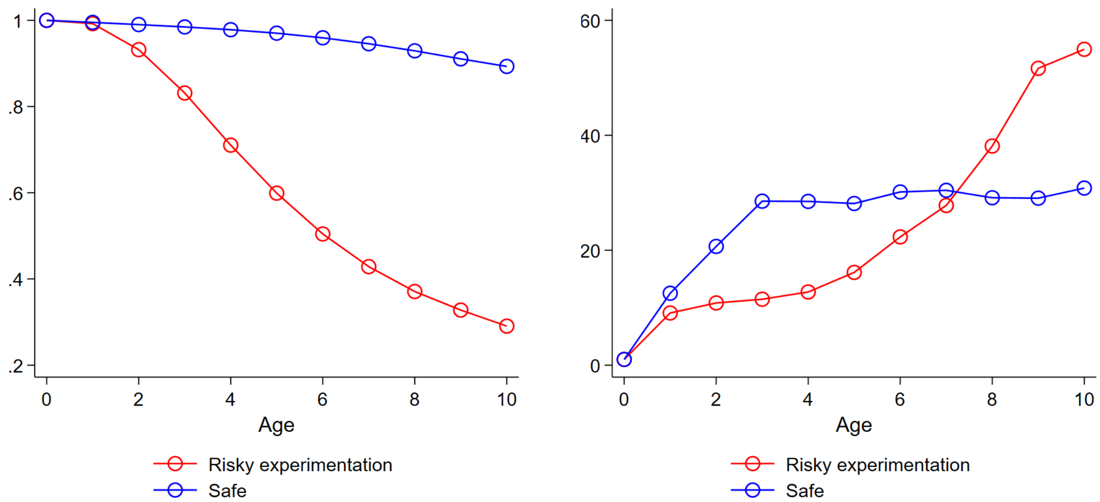
$$g_{jt} = \alpha_j + \gamma_{kt} + \beta_1 \log(size_{jt}) + \beta_2 \log(age_{jt}) + \epsilon_{jt}, \tag{13}$$

where k indexes the industry to which firm j belongs. The firm fixed effects, α_j, capture permanent productivity components that are not explained by firm size, age, or industry–year conditions. Within each entry cohort and industry, we rank firms by α_j and classify those in the top x% and bottom $(60 - x)$% of the distribution as risky experimenters. Firms with α_j values between the top x% and bottom $(60 - x)$% are classified as safe. In our baseline, we set $x = 7\%$, so that the bottom 53% and top 7% are risky experimenters, while firms between the top 7% and bottom 53% are safe. This choice is guided by our calibrated model. First, in the baseline calibration, the target share of risky experimenters among entrants is 60%, and we impose the same share in the empirical classification. Second, given our calibration of entrants' initial productivity z_e, the Pareto shape parameter ξ and the lower bound x_m, roughly the bottom 57% and top 7% of the permanent productivity distribution correspond to risky experimenters. Accordingly, we use $x = 7\%$ in the baseline and test robustness with $x = 5\%$ and $x = 3\%$.

To assess whether our empirical classification captures key life-cycle patterns implied by the model—and not directly targeted by the wage-regression specification in eq. (23)—we examine survival and relative sales by firm age. Specifically, for each age a and for both experimenting and safe firms, we plot (i) the share of surviving firms and (ii) the ratio of sales at age a to sales at age 0 ($sales_a/sales_0$). Figure 3 shows that survival declines more steeply for experimenting firms, indicating a higher exit hazard, consistent with the heavier lower tail of outcomes implied by risky experimentation. In the sales panel, conditional on survival, experimenting firms eventually outgrow safe firms and attain higher relative sales, consistent with selection on a heavier upper tail.

Building on the firms' classification derived from eq.(13), we now test whether the wage differential between experimenting and non-experimenting firms decreases as unemployment becomes less costly, proxied by higher job-finding rates. In our theoretical model, only young firms—those that have not yet drawn their permanent productivity—engage in risky experimentation. In contrast, mature firms, regardless of whether they began as safe or risky, have resolved this uncertainty and no longer take major risks, though they continue to face standard idiosyncratic shocks. Reflect-

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



ing this distinction, we restrict the sample to young firms (under three years old) and estimate variants of the following baseline regression:

$$\ln w_{it} = \eta_t + \beta X_{it} + \gamma_1 \hat{\chi}_{J(i,t)} + \gamma_2 f_{M(i,t)} + \delta(\hat{\chi}_{J(i,t)} \times f_{M(i,t)}) + \epsilon_{it}, \tag{14}$$

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

We define $f_{M(i,t)}$ as the job-finding rate from nonemployment in worker i's commuting zone $M(i,t)$, and $\hat{\chi}_{J(i,t)} \in \{0,1\}$ as the estimated experimentation indicator for the employing firm $J(i,t)$, constructed from eq. (13); $\hat{\chi}_{J(i,t)} = 1$ identifies firms classified as experimenting. The job-finding rate $f_{M(i,t)}$ is standardized—demeaned and divided by its standard deviation—to facilitate interpretation of the regression coefficients. Our main coefficient of interest is δ, which we expect to be negative.

5.2.2 Results

Table 4: Experimentation and job finding rate

Experimentation	0.0141***	0.0135***	0.0118***	0.0114***	0
	(0.00451)	(0.00450)	(0.00440)	(0.00437)	(.)
Job finding rate	0.00409**	0.00317	0.00355*	0.00548***	0.00237
	(0.00197)	(0.00194)	(0.00192)	(0.00180)	(0.00179)
Exp. × Job finding rate	-0.00457**	-0.00419**	-0.00426**	-0.00662***	-0.00324*
	(0.00195)	(0.00193)	(0.00191)	(0.00178)	(0.00186)
Observations	305199	305199	305193	304930	298067
R-squared	0.902	0.902	0.903	0.905	0.939
Time-Varying Worker Controls	No	Yes	Yes	Yes	Yes
Worker FE	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	No	No
Firm FE	No	No	No	No	Yes
Year FE	Yes	Yes	Yes	No	Yes
Year x Industry FE	No	No	No	Yes	No

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

Table 4 first shows that the coefficient on Experimentation, γ_1, is positive and statistically significant in the specifications without firm fixed effects. Since the job-finding rate is demeaned, this coefficient measures the experimenting–safe wage differential at average local job-finding conditions. The positive premium is consistent with the model: experimenting firms expose workers to greater separation risk and must compensate them through higher wages. At the same time, γ_1 is identified from cross-firm differences and should not be given a causal interpretation, since experimenting and non-experimenting firms may differ along other dimensions that affect pay. In column 5, the main effect of experimentation is absorbed by firm fixed effects, since the experimentation classification is fixed at the firm level.

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

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

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

Finally, our preferred specification in column 5 includes firm fixed effects, thus exploiting within-firm, across-worker variation in exposure to local labor-market conditions among firms that employ workers connected to different commuting zones. 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 premia fall in tighter labor markets, even when all firm-specific confounders are accounted for.

The magnitude of the interaction term is economically meaningful. In column 5, a one standard deviation increase in the job finding rate reduces the wage differential between experimental and non-experimental firms by approximately 0.3 p.p. This pattern is consistent with the mechanism in the theoretical model: when labor market conditions improve and unemployment becomes less risky, workers are more willing to accept relatively lower wages in firms pursuing uncertain but potentially high-return ventures.

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

5.3 Young-firm wage premia and job-finding rates

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

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

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

$$\ln w_{it} = \eta_t + \beta X_{it} + \gamma_1 Y_{J(i,t)} + \gamma_2 f_{M(i,t)} + \delta \left(Y_{J(i,t)} \times f_{M(i,t)} \right) + \epsilon_{it}, \tag{15}$$

where $Y_{J(i,t)}$ denotes an indicator function that equals 1 if a firm is classified as young (i.e., less than three years old). Consistent with the model's prediction, Table 8 in Appendix shows a negative and statistically significant interaction between the *Young* indicator and the local job-finding rate across specifications with worker fixed effects, rich time-varying worker controls, industry and industry×year fixed effects, and, crucially, firm fixed effects. In the most demanding designs, identification comes from *within-firm* comparisons of workers who face different outside options because they reside in different commuting zones. For an in-depth analysis on young-mature firm differentials and how they relate to job finding rates we refer to the Appendix Section B.2.

Taken together, the experimenting-versus-safe and young-versus-mature specifications point to the same equilibrium pattern: in local labor markets with better job-finding conditions, the wage premium associated with higher separation-risk firms is smaller. This pattern is present in actual employer–employee data and is robust across several specifications. Because local job-finding rates are not randomly assigned, however, these estimates remain conditional correlations: they do not by themselves identify a causal effect of the cost of unemployment on the compensation workers require for firm risk. This motivates a complementary experimental test of the worker-side mechanism.

6 A randomized survey experiment

The model's worker-side mechanism is a compensating differential. Jobs at firms with higher separation risk must offer workers a higher employment value, and the required wage differential should be smaller when unemployment is less costly. To test this mechanism directly, we design a randomized survey experiment that abstracts from the search margin and focuses on the employment-value comparison itself. Respondents are asked to compare two otherwise similar jobs that are both available to them and that differ only in firm risk and growth potential. This design mirrors the theoretical comparison in Section 2.6, where we isolate the role of expected match duration by holding fixed the worker's matching probability across contract markets. In the survey, conditioning on both jobs being available removes differences in matching probabilities from the choice problem, allowing us to elicit the wage differential that makes respondents indifferent between employment at the riskier young firm and employment at the safer firm.

The survey and register evidence play complementary roles. The register analysis documents the relevant equilibrium wage pattern in actual labor-market data, where wages reflect both workers' compensation requirements and firms' endogenous wage-setting, hiring, and entry responses. The survey experiment abstracts from these equilibrium responses, but gains experimental control over the worker-side margin that the model identifies as central: whether an increase in the cost of unemployment causally raises the compensating wage differential required for employment at a riskier firm.

6.1 Survey description

Sampling and implementation. We embedded a short research module as an addendum to Danmarks Nationalbank's *Survey of Consumers' Expectations* (*Nationalbankens forventningsundersøgelse*), a survey designed to be representative of the Danish population.[4] The survey is fielded monthly and sent to 6,000 Danish residents, comprising roughly 5,000 newly sampled individuals and about 1,000 recontacts who responded in the same month of the previous year; in a typical month, about 1,000 of the 6,000 invited individuals complete the survey. A distinctive feature of this setup is that responses can be linked, within Statistics Denmark, to administrative registers, allowing us to measure background characteristics that are not elicited in the survey itself. The module was triggered only for respondents who, in the labor–market block, reported being employed and subsequently indicated holding a *permanent* contract; only those respondents were routed to the special module. Our sampling restrictions imply roughly 600 eligible respondents per month.

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

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

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

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

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

> **Vignette.**
> Imagine that if you were to lose your job in the future, it would take you **twice/half as long** to find a new one as you wrote earlier
>
> Now suppose you work at **Company A**. Company A makes an existing, well-known product already sold on the market. Out of 100 firms of this type, about **4** close each year. It is stable and not expected to change much or grow fast. Think of yourself doing the same job you do now, just at Company A.
>
> You then receive an offer from **Company B**. Company B is developing a new, untested product that is not yet on the market. Out of 100 firms of this type, about **20** close each year. If the product succeeds, the company may grow; if it fails, it may close.
>
> When you compare the two companies, assume the working conditions are the same—same commute, working hours, coworkers, duties, and work environment. **The only differences are the chances the company could close over the next year and its potential growth.**

The failure-risk probabilities used in the vignette (4% and 20%) are chosen to be empirically plausible, based on calculations from the Danish register microdata. More importantly, the vignette should not be read as assuming that workers observe exact actuarial failure probabilities in practice. Rather, it provides transparent firm-risk information in order to standardise perceptions across respondents. This is consistent with evidence that workers and job seekers are aware of differences in employer risk, even if imperfectly: job seekers respond to signals of employer financial distress in their application behaviour, and employees also appear to learn about employer distress and reallocate in advance of shutdown (Brown and Matsa, 2016; Kostøl et al., 2024).

The vignette is phrased as a comparison between two available jobs. This framing abstracts from differences in matching probabilities across contract markets and focuses directly on the employment-value comparison. The first elicitation step asks whether, under the assigned unemployment-duration scenario, the riskier job would need to pay more, the same, or less than the safer job:

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

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

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

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

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

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

The vignette deliberately does not assign a numerical value to the growth upside of Company B. Instead, it describes the upside qualitatively while specifying the difference in closure risk. This choice lowers the cognitive burden on respondents while preserving the intended distinction between the two firm types: Company B represents a riskier young firm with higher growth potential, whereas Company A represents a safer firm. The absence of a numerical upside may affect the level of the stated risky–safe wage differential. This is not a concern for our design, because the object of interest is how this differential changes with unemployment conditions, not its absolute level. The growth narrative is held fixed across respondents, while expected unemployment duration is randomized. The experiment therefore identifies the effect of unemployment duration on the wage differential that makes workers indifferent between the risky and safe jobs.

6.2 Regression specification and result

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

Next, to address selection into survey response, we exploit the link between the survey and Danish administrative registers. This link allows us to construct respondent weights using not only standard demographic variables, but also register-based information on mortgage status and household leverage. We compute survey weights by iterative proportional fitting, or raking, based on age, gender, education, number of children, mortgage status, household leverage, and municipality. The raking targets are drawn from the population of working individuals in Denmark as of June 2025, the most recent demographic information available.

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

$$z_i = \underset{p=0.003}{\overset{\text{coef.}=5.13}{\hat{b}_D}} \Delta \ln D_i + \boldsymbol{X}_i + \varepsilon_i, \tag{16}$$

where $\boldsymbol{X}_i$ is a vector of control variables. The estimated coefficient $\hat{b}_D = 5.13$ implies that a doubling unemployment duration (i.e., lower unemployment safety) is associated with a 3.6-percentage-point ($= 5.13 \times \log 2$) increase in the compensating wage differential. This effect is statistically significant at the 1% level, with a p-value of 0.003. Note that in the calibrated model, the same elasticity can be computed, which implies that a doubling of expected unemployment duration increases the wage differential by 2.0 percentage points. Our estimate of the productivity gain from a higher job-finding rate is thus conservative.

7 Conclusion

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

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

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APPENDIX TO

Safety in Unemployment and Risky Experimentation of Young Firms

by Renato Faccini, Seho Kim, and Javier Miranda

A Appendix for model

A.1 Evolution of the distribution of firms

We denote the distribution of safe, risky young firms, and risky mature firms at the beginning of the period as $\Gamma_s(\boldsymbol{z}, n)$, $\Gamma_{ry}(\boldsymbol{z}, n)$, and $\Gamma_{rm}(\boldsymbol{z}, n)$, respectively. The distribution of safe firms, Γ_s, evolves as follows:

$$\Gamma'_s((z_e, z'_i), n') = \int \int_{n'=n^{s,*}((z_e,z_i),n)} (1 - \delta^{s,*}((z_e, z_i), n) d\Pi(z'_i|z_i) d\Gamma_s((z_e, z_i), n) + (1 - P(R)) M_e \mathbb{1}_{n=0} \mathbb{1}_{z'_i=\mu_{z_i}}). \tag{17}$$

The first term captures the mass of surviving safe firms. Firms update their temporary productivity according to $d\Pi(z'_i|z_i)$, and survive with probability $1 - \delta^*$. 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:

$$\Gamma'_{rm}((z_m, z'_i), n') = \int \int_{n'=n^{rm,*}((z_m,z_i),n)} (1 - \delta^{rm,*}((z_m, z_i), n) d\Pi(z'_i|z_i) d\Gamma_{rm}((z_m, z_i), n) + \int \int_{n'=n^{rs,*}((z_e,z_i),n)} \varphi (1 - \delta^{rs,*}((z_e, z_i), n) d\Pi_R(z_m) d\Pi(z'_i|z_i) d\Gamma_{rs}((z_e, z_i), n). \tag{18}$$

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

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

$$\Gamma'_{ry}((z_e, z'_i), n') = \int \int_{n'=n^{ry,*}((z_e,z_i),n)} (1-\varphi)(1-\delta^{ry,*}((z_e, z_i), n)d\Pi(z'_i|z_i)d\Gamma_{ry}((z_e, z_i), n) \\ + P(R)M_e \mathbb{1}_{n=0}\mathbb{1}_{z'_i=\mu_{z_i}}. \tag{19}$$

A.2 Labor market clearing

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

$$u + \int n\, d\Gamma_s(\boldsymbol{z}, n) + \int n\, d\Gamma_{ry}(\boldsymbol{z}, n) + \int n\, d\Gamma_{rm}(\boldsymbol{z}, n) = 1, \tag{20}$$

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

A.3 Social value representation

The firm's problems (6) and (7) are analytically intractable, as we need to track past contracts, which makes the state space extremely large. Kaas and Kircher (2015) show that under this type of directed-search framework, the decentralized equilibrium is efficient, and the planner's allocation can be easily analyzed through the social value representation of a firm's problem, in which the only state variables are productivity and the number of workers. Let $G^j(\boldsymbol{z}, n)$ be the social value of a firm with productivity $\boldsymbol{z}$ and n workers. It satisfies the following Bellman equation:

$$G^j(\boldsymbol{z}, n) = \max_{\delta,s,m,v} F(\boldsymbol{z}, n) - bn - f - \mu(n + \lambda(m)v) - c(v, n) \\ +\beta(1-\delta)\mathbb{E}_{z'_i|z_i} G^j(\boldsymbol{z}', n') \tag{21} \\ s.t. \\ n' = (1-s)n + mv, \quad \delta \in [\delta_0, 1], \quad s \in [s_0, 1]$$

for $j \in \{s, rm\}$. Here, μ is the Lagrange multiplier on the resource constraint in the planner's problem, which coincides with ρ when the planner's allocation is decentralized. Similarly, for risky young firms,

$$\begin{aligned} G^{ry}(\boldsymbol{z}, n) = \max_{\delta,s,m,v} & F(\boldsymbol{z}, n) - bn - f - \mu(n + \lambda(m)v) - c(v, n) \\ & +\beta(1-\delta)\mathbb{E}_{z_i'|z_i}[(1-\varphi)G^{ry}(\boldsymbol{z}', n') + \varphi\mathbb{E}_{z_m}G^{rm}(\boldsymbol{z}', n')] \\ & s.t. \\ & n' = (1-s)n + mv, \quad \delta \in [\delta_0, 1], \quad s \in [s_0, 1] \end{aligned} \tag{22}$$

Lastly, the free entry condition holds in exactly the same form as in the decentralized equilibrium,

$$\mathcal{E}_G = \sigma_\sigma \log\left(\exp\left(\frac{G^s((z_e, \mu_{z_i}), 0)}{\sigma_\sigma}\right) + \exp\left(\frac{G^{ry}((z_e, \mu_{z_i}), 0)}{\sigma_\sigma}\right)\right) = \psi_e. \tag{23}$$

We therefore solve the model via the planner's allocation, since it coincides with the decentralized equilibrium allocation.

B Appendix for empirical analysis

B.1 Robustness check

B.1.1 Young firms: less than five years old

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

Experimentation	0.00936***	0.00870**	0.00777**	0.00705**	0
	(0.00342)	(0.00340)	(0.00334)	(0.00329)	(.)
Job finding rate	0.00539***	0.00434***	0.00459***	0.00623***	0.00394***
	(0.00131)	(0.00130)	(0.00129)	(0.00126)	(0.00113)
Experimentation × Job finding rate	-0.00551***	-0.00523***	-0.00552***	-0.00709***	-0.00473***
	(0.00142)	(0.00140)	(0.00140)	(0.00132)	(0.00130)
Observations	591839	591839	591836	591558	583617
R-squared	0.884	0.885	0.886	0.887	0.921
Time-Varying Worker Controls	No	Yes	Yes	Yes	Yes
Worker FE	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	No	No
Firm FE	No	No	No	No	Yes
Year FE	Yes	Yes	Yes	No	Yes
Year x Industry FE	No	No	No	Yes	No

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

B.1.2 Experimenting firms: top 3% and bottom 57%

Table 6: Experimentation (top 3% and bottom 57%) and job finding rate

Experimentation	0.0140***	0.0139***	0.0119***	0.0119***	0
	(0.00466)	(0.00465)	(0.00457)	(0.00455)	(.)
Job finding rate	0.00437**	0.00333*	0.00375*	0.00588***	0.00291
	(0.00203)	(0.00200)	(0.00199)	(0.00188)	(0.00184)
Exp. $\times$ Job finding rate	-0.00471**	-0.00415**	-0.00426**	-0.00681***	-0.00388**
	(0.00194)	(0.00193)	(0.00191)	(0.00182)	(0.00181)
Observations	305199	305199	305193	304930	298067
R-squared	0.902	0.902	0.903	0.905	0.939
Time-Varying Worker Controls	No	Yes	Yes	Yes	Yes
Worker FE	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	No	No
Firm FE	No	No	No	No	Yes
Year FE	Yes	Yes	Yes	No	Yes
Year x Industry FE	No	No	No	Yes	No

Notes: This table presents the results for the wage premium at experimenting (defined by the top 3% and bottom 57% in α_j) young firms and its interaction with labor market conditions. The sample consists of a matched worker-year panel from 2008 to 2023, with the dependent variable being the log of yearly real hourly wages. Time-varying worker controls include worker age squared, worker age cubed, worker age interacted with education, worker age squared interacted with education and worker age cubed interacted with education. Worker age is log-transformed and normalized by 40, while education is measured in years of study and also log-transformed. In regressions with worker fixed effects, worker age and education are excluded as linear controls since they are collinear with the fixed effects. The job finding rate is calculated as the ratio of all inflows into employment divided by stock of non-employed. Note that the job finding rate is demeaned and divided by the standard deviation, so a unit increase in this rate is interpreted as a change of 1 standard deviation. Standard errors are clustered at the level of firm and worker and reported in parenthesis. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

B.1.3 Experimenting firms: top 5% and bottom 55%

Table 7: Experimentation (top 5% and bottom 55%) and job finding rate

Experimentation	0.0150***	0.0147***	0.0128***	0.0129***	0
	(0.00455)	(0.00454)	(0.00445)	(0.00442)	(.)
Job finding rate	0.00426**	0.00328*	0.00363*	0.00563***	0.00297
	(0.00201)	(0.00198)	(0.00196)	(0.00185)	(0.00182)
Exp. $\times$ Job finding rate	-0.00472**	-0.00424**	-0.00425**	-0.00666***	-0.00416**
	(0.00194)	(0.00193)	(0.00191)	(0.00180)	(0.00184)
Observations	305199	305199	305193	304930	298067
R-squared	0.902	0.902	0.903	0.905	0.939
Time-Varying Worker Controls	No	Yes	Yes	Yes	Yes
Worker FE	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	No	No
Firm FE	No	No	No	No	Yes
Year FE	Yes	Yes	Yes	No	Yes
Year x Industry FE	No	No	No	Yes	No

Notes: This table presents the results for the wage premium at experimenting (defined by the top 5% and bottom 55% in α_j) young firms and its interaction with labor market conditions. The sample consists of a matched worker-year panel from 2008 to 2023, with the dependent variable being the log of yearly real hourly wages. Time-varying worker controls include worker age squared, worker age cubed, worker age interacted with education, worker age squared interacted with education and worker age cubed interacted with education. Worker age is log-transformed and normalized by 40, while education is measured in years of study and also log-transformed. In regressions with worker fixed effects, worker age and education are excluded as linear controls since they are collinear with the fixed effects. The job finding rate is calculated as the ratio of all inflows into employment divided by stock of non-employed. Note that the job finding rate is demeaned and divided by the standard deviation, so a unit increase in this rate is interpreted as a change of 1 standard deviation. Standard errors are clustered at the level of firm and worker and reported in parenthesis. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

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

B.2.1 Empirical strategy

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

$$w_{it} = \eta_t + \beta X_{it} + \gamma_1 Y_{J(i,t)} + \gamma_2 f_{M(i,t)} + \delta \left(Y_{J(i,t)} \times f_{M(i,t)}\right) + \epsilon_{it}, \tag{24}$$

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

We test the hypothesis that the wage differential decreases with the higher job finding rates from non-employment, i.e., $\hat{\delta} < 0$. The specification in (24) 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 (24), worker fixed effects account for the time-invariant component of wages attributable to individual heterogeneity, which is similarly rewarded across employers. This component may arise from factors such as innate ability and other personal characteristics. In contrast, firm fixed effects capture the time-invariant wage component driven by employer heterogeneity, which impacts identically all employees. This could be influenced by differences in productivity, rent-sharing agreements, or workplace amenities. Year fixed effects control for time-varying earnings shifts that affect all workers simultaneously, including changes in wages related to business cycle fluctuations. The set of time-varying worker controls—including squared and cubed terms of age interacted with education—is intended to capture both general human capital accumulation over a worker's career.

B.2.2 Results

Table 8 presents the regression results examining the relationship between wages, young firm status, and local labor market conditions across five specifications. The columns progressively introduce additional controls and fixed effects to address potential sources of heterogeneity.

Table 8: Young firm and job finding rate

Young	-0.0291***	-0.0288***	-0.0262***	-0.0301***	-0.00605***
	(0.00111)	(0.00106)	(0.00101)	(0.000828)	(0.00136)
Job finding rate	0.0107***	0.00794***	0.00791***	0.00614***	0.00690***
	(0.000899)	(0.000675)	(0.000655)	(0.000387)	(0.000605)
Young × Job finding rate	-0.0107***	-0.0110***	-0.0107***	-0.00912***	-0.00618***
	(0.000983)	(0.000914)	(0.000859)	(0.000703)	(0.000645)
Observations	7730144	7730144	7730143	7730026	7711419
R-squared	0.868	0.871	0.872	0.875	0.895
Time-Varying Worker Controls	No	Yes	Yes	Yes	Yes
Worker FE	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	No	No
Firm FE	No	No	No	No	Yes
Year FE	Yes	Yes	Yes	No	Yes
Year x Industry FE	No	No	No	Yes	No

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

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

The interaction between young firm status and the job finding rate—our main object of interest—is consistently negative and highly significant across all specifications in Table 8. This robust finding indicates that the wage premium associated with working at a young firm diminishes when job-finding rates are high—that is, when labor market conditions improve and unemployment becomes less costly.

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

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

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

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

Lastly, we have verified that the results in Table 8 are robust to defining young firms using a five-year threshold (see Table 9).

Table 9: Young firm (age < 5) and job finding rate

Young	-0.0273***	-0.0272***	-0.0247***	-0.0285***	-0.00385**
	(0.00111)	(0.00105)	(0.000982)	(0.000861)	(0.00161)
Job finding rate	0.0112***	0.00843***	0.00836***	0.00658***	0.00697***
	(0.000918)	(0.000687)	(0.000666)	(0.000394)	(0.000609)
Young × Job finding rate	-0.0103***	-0.0106***	-0.0101***	-0.00841***	-0.00401***
	(0.000919)	(0.000827)	(0.000770)	(0.000679)	(0.000542)
Observations	7730144	7730144	7730143	7730026	7711419
R-squared	0.868	0.871	0.872	0.875	0.895
Time-Varying Worker Controls	No	Yes	Yes	Yes	Yes
Worker FE	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	No	No
Firm FE	No	No	No	No	Yes
Year FE	Yes	Yes	Yes	No	Yes
Year x Industry FE	No	No	No	Yes	No

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