Safety in Unemployment and Risky Experimentation of Young Firms*

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Abstract

We develop a theory in which a lower cost of job loss reduces the compensating wage premium workers require to join risky young firms. By lowering labor costs relative to safer firms, this encourages entrants to choose 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. Exceptional growth typically requires experimentation from birth—pursuing a business idea with highly uncertain market potential rather than replicating an established activity with relatively predictable outcomes (Hurst and Pugsley, 2011; Sterk et al., 2021; Akcigit and Kerr, 2018)—and these experimental strategies often fail (Kerr et al., 2014). What makes new firms experiment rather than replicate established business models?

We identify a labor-market determinant of this choice. A central but underappreciated feature of experimentation risk is that it is borne jointly: when experimentation fails, workers—not just entrepreneurs—face job loss. The cost of job loss therefore shapes the wage premium workers require to join riskier young firms. When job loss is less costly, workers require less compensation for this risk, lowering the labor costs of risky entrants relative to safer firms and making experimentation more attractive. We document this unemployment-safety 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 unemployed workers choose where to direct their search, any equilibrium contract that attracts applicants must deliver the same search value. Jobs that expose workers to greater separation risk—through layoffs or firm exit—must therefore pay higher wages to compensate workers for the capital loss incurred when they are returned to unemployment. Safer unemployment conditions reduce this capital loss. As a result, risky young firms need to pay a smaller compensating premium over safe firms. By lowering risky firms' labor costs relative to safe firms, 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 empirical and quantitative measure of unemployment safety. 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 studies the resulting propagation mechanism: higher matching efficiency raises the equilibrium job-finding rate, reduces the capital loss from job loss, and thereby lowers 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 the job finding rate, in the spirit of 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 change the cost of job loss and thereby 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 test of its wage-setting implication. The theory predicts that a higher job-finding rate lowers the cost of job loss, reducing wages at risky, experimenting young firms relative to safe young firms and thereby narrowing 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

[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).

industry–entry cohorts. Intuitively, the model maps experimentation to greater dispersion in ex-post permanent productivity; empirically, we recover each firm's permanent growth type and classify "experimenting" firms as tail types of that distribution, treating the remainder as safe.

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

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 job finding 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 relationship between local job-finding rates and wage differentials for employment at young—and, more sharply, experimenting—firms is at the heart of our theoretical mechanism. At the same time, job-finding rates are not randomly assigned, so the register-based evidence should be interpreted as conditional correlations. Hence, while the sign and robustness of the estimates are consistent with the model's unemployment-safety channel, the absence of purely exogenous variation prevents us from making definitive causal claims based on the microdata alone.

To complement the register evidence and 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. A distinctive feature of the experiment is that respondents can be linked, within Statistics Denmark, to the administrative registers used in our microdata analysis. This allows us to combine the randomized survey responses with detailed register-based demographic and financial characteristics and to construct weights that adjust for differential survey participation. The experiment varies expected unemployment duration, and therefore the cost of job loss. 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 jobs that differ in firm closure 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%. By specifying the risk difference directly, the vignette isolates the experimentation-risk margin more sharply than is possible in the register data, where experimentation must be inferred from firm outcomes or proxied by firm age. 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

[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.

acceptable discount.

Consistent with the theory, experimentally increasing expected unemployment duration raises the wage premium workers require to accept employment at the riskier young firm. A doubling of expected duration increases the required premium by about 2.3 percentage points in our baseline specification, with estimates ranging from 2.3 to 2.7 percentage points across specifications. To compare this response directly with the model, we administer the same experiment to workers in the calibrated economy: holding job characteristics and equilibrium policies fixed, we elicit the premium that makes a worker indifferent between a safe young firm and an otherwise identical risky-young firm, and then double or halve the worker's unemployment duration. The model implies an increase of about 2.0 percentage points following a doubling, closely matching the survey evidence. The experiment therefore provides causal support for the worker-side mechanism and suggests that the model does not overstate the sensitivity of wage premia to unemployment conditions. It also supports interpreting the negative relationship between job-finding rates and risky–safe wage differentials in the Danish administrative data as reflecting the channel predicted by the model. Because the model estimate lies at the lower end of the empirical range, the implied productivity effect is conservative with respect to this wage-setting margin.

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 key drivers of job creation and aggregate productivity growth (Haltiwanger et al., 2016). However, many 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 by uncovering a labor-market origin of high-growth entrepreneurship: workers share the downside risk of experimentation, and the compensation they require affects entrants' incentives to choose risky, high-upside business models. 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 unemployment safety, by reducing the cost of job loss, influences this selection margin.

Our mechanism also builds on the classic literature on compensating wage differentials. Since Rosen (1986), wage differences have been understood as equilibrium compensation for non-wage job attributes. Most directly related, Abowd and Ashenfelter (1981) study jobs that differ in anticipated unemployment and unemployment risk, showing that workers require wage compensation for exposure to temporary layoffs. We build on this foundational insight, but move it in three directions. First, we study the wage premium for job-loss risk using matched employer–employee administrative data, which allows us to relate wage differentials to firm type and local job-finding conditions. Second, we complement these equilibrium correlations with a randomized survey experiment that directly shifts expected unemployment duration and elicits the required compensation for firm risk. Third, we embed the compensating-differential mechanism in a quantitative firm-dynamics model, showing that wage premia for unemployment exposure can affect entrants' experimentation choices and, through this margin, aggregate productivity.

Our paper is also related to work showing that unemployment insurance can affect productivity by changing the composition of jobs. Most closely, Acemoglu and Shimer (1999) show that, in a directed-search environment, unemployment insurance can encourage workers to apply to higher-wage jobs with longer queues, leading firms to create more productive jobs. Our mechanism is complementary but differs along two dimensions. First, we study a firm-dynamics margin: unemployment safety affects entrants' choice between safe replication and risky experimentation, rather than only the composition of jobs offered in equilibrium. Second, within the search block, the source of the compensating differential is different. In Acemoglu and Shimer (1999), separation rates are common across jobs, so unemployment risk arises from queue length while workers are unemployed and searching. In our model, risky young firms differ from safe firms because they expose employed workers to shorter expected match duration and hence to a higher probability of being returned to unemployment. Unemployment safety lowers the compensation required for this displacement margin, reducing risky young firms' labor costs and encouraging experimentation at entry.

Our paper also contributes to the large 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 two sources: the underlying productivity distribution itself and 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 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 can reshape the productivity distribution itself. By reducing the cost of job loss, safer unemployment conditions lower the wage premium required at risky young firms and encourage entrants to choose high-upside experimentation. Relatedly, Engbom (2022) also shows that more fluid labor markets raise aggregate productivity, but through a different mechanism—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 experimentation risk is shared: not only entrepreneurs, but also their employees, are exposed to downside uncertainty. We show that labor-market institutions can encourage entrepreneurial experimentation through this employee-side margin. By reducing the cost of job loss, safer unemployment conditions lower the wage compensation needed to attract workers to risky young firms, thereby fostering experimentation through the wage-setting channel.

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

2 The model

We build on 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. 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.

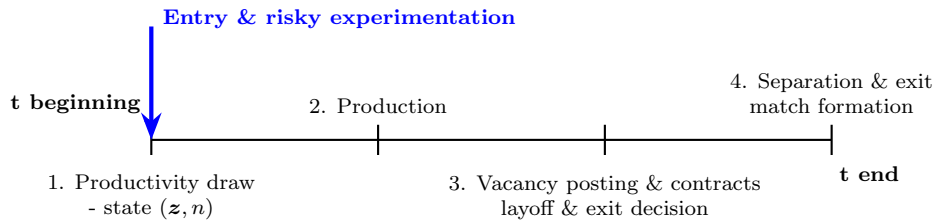
- **Risky young firms (ry)** are those that chose to experiment and have not yet matured. With probability φ, they will eventually draw a new permanent productivity level. Depending on the outcome, the firm may exit due to low productivity or continue as a mature firm—potentially becoming a superstar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

Figure 1: Timing



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, firms that have not yet reached maturity do so with probability (φ). For safe firms, maturation leaves permanent productivity unchanged at (z_e); for risky young firms, maturation resolves experimentation uncertainty through a draw of permanent productivity (z_m). Firms that are already mature retain their previously realized permanent productivity. All firms draw a persistent temporary 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 become productive only in period $t+1$, and

only if the firm survives to the next period. Thus, for a firm posting a contract with vacancy-filling probability m and current exit probability δ, an unemployed applicant starts employment at that firm next period with probability $(1-\delta)m/\lambda(m)$.

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

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

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.

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

$$V_a^j\left[\{\mathcal{C}_\tau\}_{\tau=0}^{a-1}, \{n_\tau\}_{\tau=0}^{a-1}, (z_p, z_i)\right] = \max_{\delta, m, v, \mathcal{C}_a} F((z_p, z_i), n) - W - c(v, n) - \psi_o + \beta(1-\delta)\,\mathbb{E}_{z_i'|z_i}\, V_{a+1}^j\left[\{\mathcal{C}_\tau\}_{\tau=0}^{a}, \{n_{\tau+}\}_{\tau=0}^{a}, (z_p, z_i')\right], \tag{4}$$

subject to

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

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

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

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:

$$V_a^{ry}\left[\{\mathcal{C}_\tau\}_{\tau=0}^{a-1},\{n_\tau\}_{\tau=0}^{a-1},(z_p,z_i)\right]=\max_{\delta,m,v,\mathcal{C}_a} F((z_p,z_i),n)-W-c(v,n)-\psi_o$$
$$+\beta(1-\delta)\,\mathbb{E}_{z_i'|z_i}\left[(1-\varphi)V_{a+1}^{ry}\left[\{\mathcal{C}_\tau\}_{\tau=0}^{a},\{n_{\tau+}\}_{\tau=0}^{a},(z_p,z_i')\right]\right.$$
$$\left.+\varphi\mathbb{E}_{z_m}V_{a+1}^{rm}\left[\{\mathcal{C}_\tau\}_{\tau=0}^{a},\{n_{\tau+}\}_{\tau=0}^{a},(z_m,z_i')\right]\right], \quad (5)$$

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:

$$\mathcal{E}=\mathbb{E}_\epsilon\left[\max\left(\mathcal{E}^s+\epsilon,\mathcal{E}^{ry}\right)\right], \quad (6)$$

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:

$$\mathcal{E} = \sigma_\sigma \log\left(\exp\left(\frac{\mathcal{E}^s}{\sigma_\sigma}\right) + \exp\left(\frac{\mathcal{E}^{ry}}{\sigma_\sigma}\right)\right), \tag{7}$$

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

$$P(R) = \frac{\exp\left(\frac{\mathcal{E}^{ry}-\mathcal{E}^s}{\sigma_\sigma}\right)}{1+\exp\left(\frac{\mathcal{E}^{ry}-\mathcal{E}^s}{\sigma_\sigma}\right)}, \tag{8}$$

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 Wage setting and the unemployment-safety channel

We now specialize the general long-term contract to a flat-wage contract: as long as a worker remains with the firm, she receives a constant wage, w_ι. Iterating the employment value (3) forward yields

$$E^j(\boldsymbol{z}, n; \mathcal{C}_\iota) - U = A_\iota(\boldsymbol{z}, n)\left[w_\iota - (1-\beta)U\right], \tag{9}$$

where $A_\iota(\boldsymbol{z}, n) = 1 + \beta p_{\varsigma_\iota}(\boldsymbol{z}, n)\mathbb{E}_{z_\iota} A_\iota(\boldsymbol{z}', n')$ is the expected discounted duration of the match under contract $\mathcal{C}_\iota$.

Substituting (9) into the worker-attraction condition (2) gives the flow wage

$$w_\iota = b + \rho + \frac{1}{\beta(1-\delta_\iota)}\frac{\lambda(m_\iota)}{m_\iota}\frac{\rho}{\mathbb{E}_{z_\iota} A'_\iota}. \tag{10}$$

The wage has two components. The first, $b + \rho = (1-\beta)U$, compensates the worker for the flow value of unemployment. The second delivers the employment surplus required by the worker-attraction condition. A firm that wants to fill vacancies faster must attract a longer queue, reducing each applicant's probability of obtaining the job and requiring higher wage compensation conditional on matching. The literature has largely emphasized this queue-length term, $\lambda(m_\iota)/m_\iota$. Our mechanism instead operates through expected match duration, $\mathbb{E} * z * \iota A'_\iota$: shorter matches require a higher flow wage to deliver the same surplus.

To isolate this risk-compensation channel, suppose temporarily that vacancy-

creation costs are linear. All firms then choose the same vacancy-filling rate, so the worker matching rate, $m/\lambda(m)$, is common across firm types. The wage differential between risky and safe young firms is therefore

$$w_{ry} - w_s = \underbrace{\frac{\rho}{\beta}\frac{\lambda(m)}{m}}_{\substack{\text{capital loss} \\ \text{from job loss}}} \underbrace{\left[\frac{1}{(1-\delta_{ry})\mathbb{E}_{z_{ry}}A'_{ry}} - \frac{1}{(1-\delta_s)\mathbb{E}_{z_s}A'_s}\right]}_{\substack{\text{differential exposure} \\ \text{to job loss}}}. \tag{11}$$

The first term is the capital loss associated with being returned to unemployment. Indeed, the worker-attraction condition implies

$$\frac{\rho}{\beta}\frac{\lambda(m)}{m} = (1-\delta_\iota)\left[\mathbb{E}_{z_\iota}E^j(\boldsymbol{z}', n'; \mathcal{C}_\iota) - U\right].$$

It is the gain from leaving unemployment and becoming employed, and hence the loss incurred when employment ends.

The second term captures the greater exposure of workers at risky young firms to this loss. Because risky young firms offer shorter expected match durations, $(1-\delta_{ry})\mathbb{E}_{z_{ry}}A'_{ry} < (1-\delta_s)\mathbb{E}_{z_s}A'_s$, the differential-exposure term is positive and $w_{ry} > w_s$.

Equation (11) conveys the key insight of the paper: a lower cost of job loss reduces the compensating wage premium for experimentation. Everything else equal, a higher worker matching rate, $m/\lambda(m)$, raises the probability of reemployment and makes the gain from employment easier to realize. This lowers the capital loss from job loss and therefore the risky–safe wage differential.

In general equilibrium, however, the search value ρ, expected match durations, and firm policies also adjust. Equation (11) therefore identifies the direct wage-setting effect, while the next section evaluates the full equilibrium response numerically. In the calibrated model, higher matching efficiency raises the job-finding rate and reduces the risky–safe wage differential. The resulting decline in risky firms' relative labor costs raises the value of experimentation and, through equation (8), increases the share of risky entrants.

We focus on the job-finding rate because it provides a direct empirical counterpart that can be measured in the data. Unemployment benefits operate through a similar mechanism: by raising the value of unemployment, they reduce the capital loss from job loss and therefore lower the compensation workers require for greater exposure to displacement.

3 Mapping the model to data

Computation The decentralized equilibrium is not directly tractable 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. We can therefore compute the allocation 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 targeted 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. The job finding rate affects 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, wage-premium changes induced by job-finding conditions 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.

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

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		

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 therefore raises the worker's matching probability $m/\lambda(m)$. In equilibrium, this improves workers' job-finding conditions. Importantly, the parameter k enters the decentralized firm problem—equations (4) and (5)—only through $\lambda(m)$ in the worker-attraction constraint. Lowering k therefore changes the employment value, and hence the wage, that firms must offer to attract workers under safer job-finding conditions. We use this counterfactual 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

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.

in k, affects wages, experimentation, and the composition of firms. The overall effects of the counterfactual 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, shorter expected match durations make young-firm wages more exposed to the unemployment-safety channel, dampening their average wage increase relative to mature firms. 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 at a larger scale, which lowers productivity for a given level of aggregate employment. Finally, allocative efficiency rises by about 0.4%. Higher matching efficiency reduces the wage cost of attracting workers at a given vacancy-filling probability, allowing firms with stronger incentives to expand to hire more easily and reducing the dispersion in marginal products across firms.

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.

A Testable Implication The model experiment above shows that an increase in the job-finding rate, driven by higher matching efficiency, raises entrants' incentive to choose risky experimentation, ultimately increasing aggregate 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 pay a smaller wage premium over 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 wage-setting outcomes vary with local job-finding rates in a way that is consistent with our mechanism. Using Danish administrative data and geographic variation in job-finding rates across commuting zones, we examine whether, among young firms, wages at experimenting firms are lower relative to non-experimenting firms 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 firms with higher separation risk need to pay a smaller compensating premium. This is the comparative static reported in Table 2, where a higher average job-finding rate is associated with a lower wage of risky entrants relative to safe entrants. We take this prediction 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:

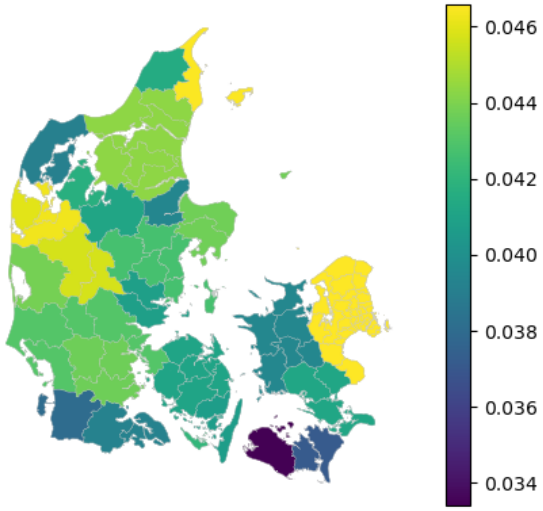
Employment Registry: The *Beskæftigelse for Lønmodtagere* (BFL) dataset contains monthly information for all workers residing in Denmark, including details about their employers, salaries, hours worked as well as job start and end dates, covering the period from 2008 to 2023.

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.

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.

Figure 2: Job finding rate by commuting zone



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.

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 $x = 3\%$.

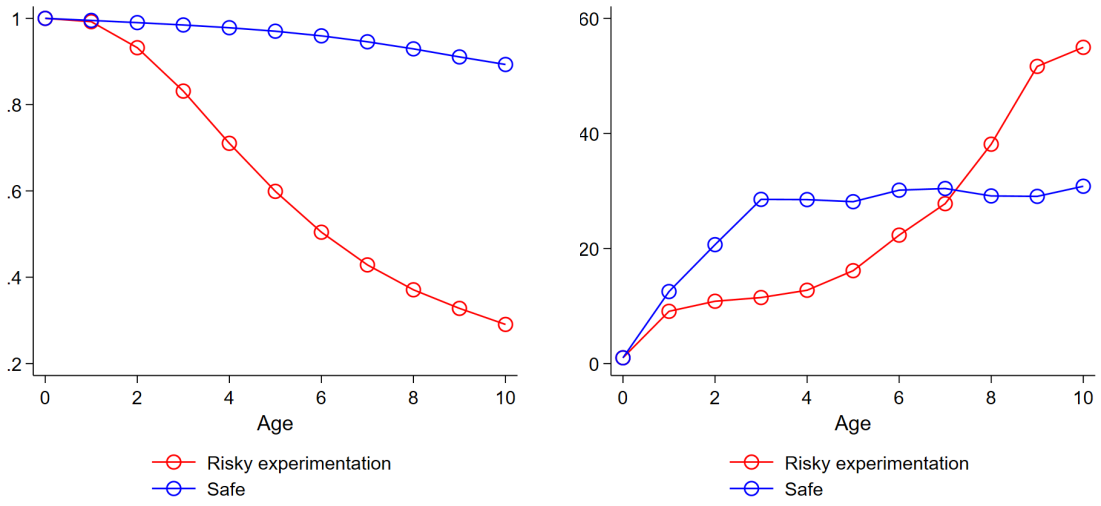
To assess whether our empirical classification captures key life-cycle patterns implied by the model—and not directly targeted by the wage-regression specification in eq. (23)—we examine survival and relative sales by firm age. Specifically, for each age a and for both experimenting and safe firms, we 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 job loss becomes less costly, proxied by higher job-finding rates. In our theoretical model, only young firms—those that have not yet drawn their permanent productivity—engage in risky experimentation. In contrast, mature firms, regardless of whether they began as safe or risky, have resolved this uncertainty and no longer take major risks, though they continue to face standard idiosyncratic shocks. Reflecting this distinction, we restrict the sample to young firms (under three years old) and estimate variants of the following baseline regression:

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

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

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



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 reports the baseline wage regressions estimated on the sample of young firms. All specifications include worker fixed effects, so the estimates absorb permanent differences across workers, such as ability, persistent earnings capacity, and stable preferences over job-loss risk. This is important because workers with different tolerance for risk may sort differently across experimenting and non-experimenting firms. Starting in column 2, we also add time-varying worker controls, allowing wage profiles

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.

to vary flexibly with age and education. The specifications include year fixed effects, except in column 4 where year effects are absorbed by industry-by-year fixed effects. We begin with the average wage premium at experimenting firms. 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 exper-

imenting 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, the source of identifying variation 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 pattern is consistent with the model's prediction that experimentation-related wage premia are lower in labor markets with higher job-finding rates, even after accounting for time-invariant firm-specific confounders.

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 experimenting and non-experimenting firms by approximately 0.3 p.p. This pattern is consistent with the mechanism in the theoretical model: when job-finding conditions improve, job loss becomes less costly, and workers require a smaller compensating premium to accept employment at firms pursuing uncertain but potentially high-return business strategies.

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 through higher matching efficiency increases average wages at young firms by less than wages at mature firms. The model therefore predicts 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). The sequence of specifications mirrors the progression used in Table 4: we start from worker and year fixed effects, then add time-varying

worker controls, industry fixed effects, industry-by-year fixed effects, and finally firm fixed effects. Consistent with the model's prediction, Table 11 in the Appendix shows that the interaction between the *Young* indicator and the local job-finding rate is negative and statistically significant at the 1% level in every specification, including the specification with firm fixed effects. In this most demanding design, identification comes from within-firm comparisons of workers who face different outside options because they reside in different commuting zones. For a fuller analysis of young–mature wage differentials and their relationship with local job-finding rates, we refer to Appendix Section B.2.

Across both exercises, 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 appears 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 job-finding conditions 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 predicts that a job with a shorter expected match duration must offer a higher flow wage to deliver the same employment value, and that this compensating differential rises when unemployment becomes more costly. To test this worker-side mechanism causally, we design a randomized survey experiment. Respondents compare two available jobs that differ in firm closure risk and growth potential but are otherwise identical, and are randomly assigned a hypothetical unemployment duration following job loss equal to either half or twice their own expected duration. We then elicit the wage differential that makes respondents indifferent between employment at the riskier young firm and employment at the safer firm, and test whether this differential rises when expected unemployment duration increases.

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 workers' compensation requirements together with firms' endoge-

nous 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 job loss causally raises the compensating wage differential required for employment at a riskier firm. It also allows us to represent experimentation risk directly in the choice environment, whereas in the register data experimentation must necessarily be inferred from imperfect proxies such as ex-post firm outcomes or firm age.

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. We fielded the module in four consecutive monthly waves, from January to April 2026, yielding roughly 2,400 eligible respondents in total.

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 unemployment duration if they lost their job, (ii) are randomly assigned to a hypothetical scenario in which this duration is either halved or doubled, (iii) read a vignette contrasting a stable firm and an experimental young firm under the assigned unemployment-duration scenario, and (iv) indicate the pay change that would make them switch. Each respondent answers

[4]The survey module was pre-registered in the AEA RCT Registry (Faccini, Renato and Seho Kim, 2026).

a single vignette question; no follow-up or re-elicitation is made.

The model and register-based empirical analysis use the job-finding rate as the key measure of unemployment safety. In the survey, we instead phrase the treatment in terms of expected unemployment duration, because this is easier for respondents to reason about. The two objects map directly into each other: under a constant job-finding hazard, expected unemployment duration satisfies ($D = 1/f$). Thus, a longer expected unemployment duration corresponds to a lower job-finding rate and a higher cost of job loss.

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

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

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

> **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.

Table 5 reports summary statistics for the survey responses. Respondents expect an average unemployment duration of 4.4 months and require, on average, a 16.2% wage premium to move from the safe to the risky firm. The corresponding standard deviations are 5.4 months and 17.6 percentage points, indicating substantial heterogeneity across respondents.

Table 5: Summary statistics: survey

	Mean	SD	P10	Median	P90	N
Unemployment duration (months)	4.43	5.41	1.00	3.00	10.00	2559
$\Delta w^{\text{risky–safe}}$ (%)	16.24	17.60	0.00	15.00	30.00	2559

Notes: This table presents summary statistics of the responses from the survey. Unemployment duration is what respondents answer (in months) in Q1, and $\Delta w^{\text{risky–safe}}$ (in percent) is the reservation premium/discount in Q2b. We winsorize the data at the top and bottom 1%.

6.2 Regression specification and result

Let D_i denote respondent i's expected unemployment duration, elicited in Q1. The experiment randomly assigns a proportional change $\Delta \ln D_i \in \{-\ln 2, \ln 2\}$, corresponding to a halving or doubling of expected duration. Let z_i denote the compensating wage differential elicited in Q2b, defined as $z_i \equiv 100\,(\log w_{i1} - \log w_{i0})$, where w_{i1} and w_{i0} are the wages respondent i would require at the risky and safe young firm, respectively. The survey elicits z_i directly rather than the two wage levels separately.

A distinctive feature of the survey is that responses can be linked, within Statistics Denmark, to administrative registers. This linkage provides demographic and financial characteristics not elicited in the survey module and allows us to correct for differential survey response using register-based weights. The regressions include controls for age, number of children, income, mortgage status, and household leverage, together with gender, commuting-zone, and education fixed effects. We construct survey weights using iterative proportional fitting (raking) over age, gender, education, number of children, income, mortgage status, and household leverage. The target margins are computed from the population of employed individuals in Denmark using the most recent demographic information available, as of June 2025.

Motivated by the model, we begin with a parsimonious specification in which the wage premium depends on the proportional change in expected unemployment duration:

$$z_i = \alpha + \beta_D \Delta \ln D_i + \gamma' \boldsymbol{X} * i + \varepsilon_i, \tag{16}$$

where $\boldsymbol{X} * i$ is a vector of control variables. The coefficient β_D is the semi-elasticity of the wage premium with respect to expected unemployment duration: it measures the change in the premium, in percentage points, associated with a one-log-point increase in duration. Because $\Delta \ln D_i$ is randomly assigned, β_D has a causal interpretation.[5]

The semi-elasticity may nevertheless vary with respondents' baseline unemployment prospects. In particular, the effect of doubling expected unemployment duration may be larger for respondents who initially expect a long unemployment spell. We therefore also estimate the fully interacted specification

$$z_i = \alpha + \beta_D \Delta \ln D_i + \theta \widetilde{\ln D_i} + \beta_H \left(\widetilde{\ln D_i} \times \Delta \ln D_i \right) + \gamma' \boldsymbol{X}_i + \varepsilon_i, \tag{17}$$

where $\widetilde{\ln D_i} \equiv \ln D_i - \overline{\ln D}$ denotes demeaned baseline unemployment duration. In this specification, β_D measures the causal semi-elasticity for a respondent with average baseline duration, while β_H captures how the treatment effect varies with baseline duration. Including the main effect of baseline duration also absorbs cross-sectional variation in required premia associated with respondents' unemployment prospects, which may reflect characteristics such as employability, pessimism, or risk preferences.

[5] According to the wage equation (10), $z_i \approx 100 \times (w^{\text{risky}} - w^{\text{safe}})/w^{\text{safe}} = 100 c_1 D/(c_2 + c_3 D)$, where $D = \lambda(m)/m$, $c_1 = \frac{\rho}{\beta}\left(\frac{1}{(1-\delta*ry)\mathbb{E}A*ry'} - \frac{1}{(1-\delta_s)\mathbb{E}A'_s}\right)$, $c_2 = b + \rho$, and $c_3 = \frac{\rho}{\beta}\frac{1}{(1-\delta_s)\mathbb{E}A'_s}$, with $c_1, c_2, c_3 > 0$. The wage premium is therefore increasing and concave in D, motivating a log-linear approximation over the range of durations observed in the survey.

Table 6: Regression results: survey and hypothetical vignettes

$\Delta \ln D_i$	3.325***	3.863***	3.709***	3.404***
	(0.879)	(0.979)	(0.933)	(0.881)
$(\ln D_i \times \Delta \ln D_i)$		0.400	1.004	1.306
		(0.988)	(0.896)	(0.906)
Observations	2556	2559	2559	2556
R-squared	0.0814	0.0420	0.0768	0.0997
Weighted	Yes	Yes	Yes	Yes
Fixed effects	Yes	No	Yes	Yes
Controls	Yes	No	No	Yes

Notes: This table presents the regression results with randomized hypothetical vignettes in the survey. 'Weighted' indicates that the observations are weighted by the survey weights using raking. 'Fixed effects' indicates that we add commuting zone, gender, and education fixed effects. Controls include age, number of children, income, mortgage status, and household leverage. For the specifications with interactions, we subtract the mean of $\ln D_i$ from $\ln D_i$ for ease of interpretation, and we also control for the demeaned unemployment duration itself. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Because baseline duration is not randomly assigned, however, θ is not given a causal interpretation.

Table 6 presents the results. Column 1 reports the parsimonious specification in equation (16), including the fixed effects and additional controls. The remaining columns report the fully interacted specification in equation (17), varying the inclusion of fixed effects and controls. The estimated coefficient on $\Delta \ln D_i$ is positive and statistically significant across specifications. In column 1, the estimate of 3.325 implies that, under the log-linear approximation, doubling expected unemployment duration relative to leaving it unchanged raises the required wage premium by approximately $3.325 \times \ln 2 = 2.3$ percentage points. The estimated interaction coefficients are positive but statistically insignificant. We therefore cannot reject the parsimonious specification in which the semi-elasticity is constant across baseline unemployment durations.

Quantitative comparison across approaches. We next compare the sensitivity of the risky–safe wage premium to expected unemployment duration across the model, the administrative data, and the survey. To construct a model counterpart of the survey estimate, we effectively administer the experiment to workers employed at safe young firms in the baseline economy. For each safe-firm state x, we take the

equilibrium wage $w_s(x)$ and construct a risky-young clone with the same current state variables but the continuation process and job-loss risk of a risky young firm. We then calculate the counterfactual wage $w^*_{ry}(x, D)$ that equates the two employment values, $E_{ry}(x; w^*_{ry}(x, D), U(D)) = E_s(x; w_s(x), U(D))$. As in the survey vignette, the worker faces the same expected unemployment duration following job loss from either firm. We randomly assign model workers to a doubling or halving of unemployment duration, implemented by respectively halving or doubling their personal job-finding rate, holding everything else constant. We then construct the reservation premium $z_x(D) = 100[\ln w^*_{ry}(x, D) - \ln w_s(x)]$, weight observations by employment at safe young firms, and estimate the same regression as in the survey. This model-survey exercise implies that doubling expected unemployment duration raises the required wage premium by 2.03 percentage points.

The administrative data provide a complementary equilibrium benchmark. Table 4 shows that a one-standard-deviation increase in the local job-finding rate lowers the wage differential between experimenting and non-experimenting young firms by 0.32 to 0.66 percentage points. Our preferred estimate is the 0.324-percentage-point effect from the specification with firm fixed effects, which absorbs persistent firm-level determinants of wages and identifies the coefficient from variation in local job-finding conditions across workers employed by the same firm. Given a mean job-finding rate of 0.0469 and a standard deviation of 0.0042, the corresponding semi-elasticity is $-0.324/[\ln(1/(0.0469 + 0.0042)) - \ln(1/0.0469)] = 3.78$. A doubling of expected unemployment duration therefore implies an increase in the wage differential of $3.78 \ln 2 = 2.62$ percentage points. Alternative administrative specifications imply effects of up to 5.33 percentage points.

Table 7 compares the implied effect of doubling expected unemployment duration across the three approaches. The required premium increases by 2.03 percentage points in the model-survey exercise, by 2.62 percentage points in our preferred administrative specification, and by between 2.30 and 2.68 percentage points in the survey. The preferred estimates are therefore tightly clustered between approximately 2 and 2.7 percentage points. The model and survey estimates measure directly comparable worker-side reservation-wage responses, since both hold the two job offers fixed and vary only the worker's unemployment prospects. The administrative estimate instead captures an equilibrium wage relationship and remains a conditional correlation, so it provides a complementary quantitative benchmark rather than an identical causal ob-

ject. The close correspondence suggests that the calibrated model does not overstate the sensitivity of the compensating wage premium to unemployment duration. Since the model estimate lies at the lower end of the empirical range, the approximately 1% productivity effect may be viewed as conservative with respect to the worker-side wage-setting channel, holding the model's other margins fixed.

Table 7: Comparison of how the wage premium reacts to unemployment duration

	Model	Administrative data	Survey
$\beta_D \times \ln(2)$	2.03	$2.61 \sim 5.33$	$2.30 \sim 2.68$

7 Conclusion

This paper proposes a mechanism linking the cost of job loss to aggregate productivity through the risky experimentation of new entrants. We develop a heterogeneous-firm model with a frictional labor market and 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—are smaller where job-finding rates are higher, consistent with the model's unemployment-safety channel. A randomized module embedded in Danmarks Nationalbank's Survey of Consumers' Expectations provides causal support for the worker-side mechanism: exogenously increasing expected unemployment duration raises the wage differential required to accept employment at riskier firms. Overall, the register and survey evidence support the view that a lower cost of job loss encourages risky experimentation and enhances long-run productivity.

Our findings suggest that institutional environments that improve job-finding prospects can raise productivity by reducing the compensating wage premium required at risky 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—such as unemployment-insurance design, activation and placement services, training policies, 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 creating scope for new entrants and business models, and where labor-market institutions may shape how readily transformative firms emerge and scale.

References

Abowd, J. M. and O. C. Ashenfelter (1981). Anticipated unemployment, temporary layoffs, and compensating wage differentials. In S. Rosen (Ed.), *Studies in Labor Markets*, pp. 141–170. Chicago: University of Chicago Press.

Abowd, J. M., F. Kramarz, and D. N. Margolis (1999). High wage workers and high wage firms. *Econometrica 67*(2), 251–333.

Acemoglu, D. and R. Shimer (1999). Efficient unemployment insurance. *Journal of political Economy 107*(5), 893–928.

Akcigit, U., H. Alp, J. G. Pearce, and M. Prato (2025). Transformative and subsistence entrepreneurs: Origins and impacts on economic growth.

Akcigit, U. and W. R. Kerr (2018). Growth through heterogeneous innovations. *Journal of Political Economy 126*(4), 1374–1443.

Babina, T., W. Ma, C. Moser, P. Ouimet, and R. Zarutskie (2019). Pay, employment, and dynamics of young firms. *Kenan Institute of Private Enterprise Research Paper* (19-25).

Bianchi, M. and M. Bobba (2013). Liquidity, risk, and occupational choices. *Review of Economic Studies 80*(2), 491–511.

Bilal, A. (2023). The geography of unemployment. *The Quarterly Journal of Economics 138*(3), 1507–1576.

Bilal, A., N. Engbom, S. Mongey, and G. L. Violante (2022). Firm and worker dynamics in a frictional labor market. *Econometrica 90*(4), 1425–1462.

Brown, J. and D. A. Matsa (2016). Boarding a sinking ship? an investigation of job applications to distressed firms. *The Journal of Finance 71*(2), 507–550.

Buera, F. J., J. P. Kaboski, and Y. Shin (2011). Finance and development: A tale of two sectors. *American economic review 101*(5), 1964–2002.

Chava, S. and M. R. Roberts (2008). How does financing impact investment? the role of debt covenants. *The Journal of Finance 63*(5), 2085–2121.

Chodorow-Reich, G. (2014). The employment effects of credit market disruptions:

Firm-level evidence from the 2008–9 financial crisis. *The Quarterly Journal of Economics 129*(1), 1–59.

Choi, J. (2017). Entrepreneurial risk-taking, young firm dynamics, and aggregate implications.

Cooper, R., J. C. Haltiwanger, and J. Willis (2004). Dynamics of labor demand: evidence from plant-level observations and aggregate implications.

Darougheh, S., R. Faccini, L. Melosi, and A. T. Villa (2024). On-the-job search and inflation under the microscope.

David, J. M., H. A. Hopenhayn, and V. Venkateswaran (2016). Information, misallocation, and aggregate productivity. *The Quarterly Journal of Economics 131*(2), 943–1005.

Davis, S. J., J. C. Haltiwanger, and S. Schuh (1998). Job creation and destruction. *MIT Press Books 1*.

Engbom, N. (2022). Labor market fluidity and human capital accumulation. Technical report, National Bureau of Economic Research.

Faccini, Renato and Seho Kim (2026). "Labor Market Institutions and the Success of Startups". AEA RCT Registry. January 09. https://doi.org/10.1257/rct.17593-1.0.

Fan, W. and M. J. White (2003). Personal bankruptcy and the level of entrepreneurial activity. *The Journal of Law and Economics 46*(2), 543–567.

Gertler, M. and S. Gilchrist (1994). Monetary policy, business cycles, and the behavior of small manufacturing firms. *The Quarterly Journal of Economics 109*(2), 309–340.

Gottlieb, J. D., R. R. Townsend, and T. Xu (2022). Does career risk deter potential entrepreneurs? *The Review of Financial Studies 35*(9), 3973–4015.

Haltiwanger, J., R. S. Jarmin, R. Kulick, and J. Miranda (2016). High growth young firms: contribution to job, output, and productivity growth. In *Measuring entrepreneurial businesses: Current knowledge and challenges*, pp. 11–62. University of Chicago Press.

Hombert, J., A. Schoar, D. Sraer, and D. Thesmar (2020). Can unemployment insurance spur entrepreneurial activity? evidence from france. *The Journal of Finance 75*(3), 1247–1285.

Hopenhayn, H. and R. Rogerson (1993). Job turnover and policy evaluation: A general equilibrium analysis. *Journal of political Economy 101*(5), 915–938.

Hsieh, C.-T. and P. J. Klenow (2009). Misallocation and manufacturing tfp in china and india. *The Quarterly journal of economics 124*(4), 1403–1448.

Hurst, E. and B. W. Pugsley (2011). What do small businesses do? *Brookings Papers on Economic Activity 2011*(2), 73–118.

Kaas, L. and P. Kircher (2015). Efficient firm dynamics in a frictional labor market. *American Economic Review 105*(10), 3030–3060.

Kerr, W. R. and R. Nanda (2015). Financing innovation. *Annual Review of Financial Economics 7*(1), 445–462.

Kerr, W. R., R. Nanda, and M. Rhodes-Kropf (2014). Entrepreneurship as experimentation. *Journal of Economic Perspectives 28*(3), 25–48.

Khan, A. and J. K. Thomas (2013). Credit shocks and aggregate fluctuations in an economy with production heterogeneity. *Journal of Political Economy 121*(6), 1055–1107.

Kim, S. (2025). Workers' job prospects and young firm dynamics.

Kostøl, A. R., M. C. Merkle, and M. Grindaker (2024, October). Layoff costs and learning about employer financial distress. IZA Discussion Paper 17340, IZA.

Midrigan, V. and D. Y. Xu (2014). Finance and misallocation: Evidence from plant-level data. *American economic review 104*(2), 422–458.

Nanda, R. and M. Rhodes-Kropf (2013). Investment cycles and startup innovation. *Journal of Financial Economics 110*(2), 403–418.

Petrongolo, B. and C. A. Pissarides (2001). Looking into the black box: A survey of the matching function. *Journal of Economic literature 39*(2), 390–431.

Pries, M. and R. Rogerson (2005). Hiring policies, labor market institutions, and labor market flows. *Journal of Political Economy 113*(4), 811–839.

Restuccia, D. and R. Rogerson (2017). The causes and costs of misallocation. *Journal of Economic Perspectives 31*(3), 151–174.

Rosen, S. (1986). The theory of equalizing differences. In O. C. Ashenfelter and R. Layard (Eds.), *Handbook of Labor Economics*, Volume 1, Chapter 12, pp. 641–692. Amsterdam: North-Holland.

Schoar, A. (2010). The divide between subsistence and transformational entrepreneurship. *Innovation policy and the economy 10*(1), 57–81.

Sterk, V., P. Sedláček, and B. Pugsley (2021). The nature of firm growth. *American*

Economic Review 111(2), 547–579.

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:

$$\Gamma'_s((z_e, z'_i), n') = \int \int_{n'=n^{s,*}((z_e,z_i),n)} (1-\delta^{s,*}((z_e, z_i), n) d\Pi(z'_i|z_i) d\Gamma_s((z_e, z_i), n) + (1-P(R))M_e \mathbb{1}_{n=0} \mathbb{1}_{z'_i=\mu_{z_i}}). \tag{18}$$

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:

$$\begin{aligned}\Gamma'_{rm}((z_m, z'_i), n') = &\int \int_{n'=n^{rm,*}((z_m,z_i),n)} (1-\delta^{rm,*}((z_m, z_i), n) d\Pi(z'_i|z_i) d\Gamma_{rm}((z_m, z_i), n) \\ &+ \int \int_{n'=n^{rs,*}((z_e,z_i),n)} \varphi(1-\delta^{rs,*}((z_e, z_i), n) d\Pi_R(z_m) d\Pi(z'_i|z_i) d\Gamma_{rs}((z_e, z_i), n).\end{aligned} \tag{19}$$

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:

$$\Gamma'_{ry}((z_e, z'_i), n') = \int \int_{n'=n^{ry,*}((z_e,z_i),n)} (1-\varphi)(1-\delta^{ry,*}((z_e,z_i),n) d\Pi(z'_i|z_i) d\Gamma_{ry}((z_e,z_i),n) + P(R)M_e \mathbb{1}_{n=0} \mathbb{1}_{z'_i=\mu_{z_i}}. \tag{20}$$

A.2 Labor market clearing

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

$$u + \int n \, d\Gamma_s(\boldsymbol{z}, n) + \int n \, d\Gamma_{ry}(\boldsymbol{z}, n) + \int n \, d\Gamma_{rm}(\boldsymbol{z}, n) = 1, \tag{21}$$

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 (4) and (5) 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:

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

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 decentral-

ized. Similarly, for risky young firms,

$$\begin{aligned} G^{ry}(\boldsymbol{z}, n) = \max_{\delta,s,m,v} & F(\boldsymbol{z}, n) - bn - f - \mu(n + \lambda(m)v) - c(v, n) \\ & + \beta(1-\delta)\mathbb{E}_{z_i'|z_i}[(1-\varphi)G^{ry}(\boldsymbol{z}', n') + \varphi\mathbb{E}_{z_m}G^{rm}(\boldsymbol{z}', n')] \qquad (23) \\ & s.t. \\ & n' = (1-s)n + mv, \quad \delta \in [\delta_0, 1], \quad s \in [s_0, 1] \end{aligned}$$

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

$$\mathcal{E}_G = \sigma_\sigma \log\left(\exp\left(\frac{G^s((z_e, \mu_{z_i}), 0)}{\sigma_\sigma}\right) + \exp\left(\frac{G^{ry}((z_e, \mu_{z_i}), 0)}{\sigma_\sigma}\right)\right) = \psi_e. \qquad (24)$$

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 8: 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 9: 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. × 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 10: 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. × 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:

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

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 (25) 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 (25), 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 11 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 11: 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 11. This robust finding indicates that the wage premium associated with working at a young firm diminishes when job-finding rates are high—that is, when labor market conditions improve and unemployment becomes less costly.

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

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

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

In the counterfactual experiment of Section 4 where we reduce hiring costs, the model predicts a 21.1% rise in the job-finding rate and a 0.654 p.p. decline in the young-firm wage premium. This corresponds to an elasticity that is about twice as large as the one estimated from the data. However, it is important to note that the model targets unemployment-to-employment transitions, while the empirical measure

is based on inflows from non-employment, which include both unemployed and inactive individuals. Since the inactive are typically less responsive to labor market conditions, the empirical elasticity likely understates the true responsiveness. Taking this into account—along with the uncertainty around the estimates—the magnitude implied by the model appears broadly in line with the empirical evidence.

Lastly, we have verified that the results in Table 11 are robust to defining young firms using a five-year threshold (see Table 12).

Table 12: 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.