

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. Lower labor costs encourage high-upside experimentation and raise productivity. Because experimentation is not directly observable, we exploit its life-cycle structure: experimentation risk is concentrated among young firms and resolved as firms mature. Using Danish matched employer–employee data and labor-market variation, we show that higher job-finding rates are associated with a lower young–mature wage differential. A randomized survey experiment supports the mechanism: worsening unemployment prospects increases the 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 aggregate productivity growth, yet they are rare ([Haltiwanger et al., 2016](#); [Sterk et al., 2021](#)). Growth of this kind typically begins as an experiment: a business idea whose market potential is unknown, where most such ideas fail and only a few grow very large ([Kerr et al., 2014](#)). Many entrants do not attempt it, replicating an established activity with relatively predictable outcomes instead ([Hurst and Pugsley, 2011](#)). What leads new firms to choose risky experimentation over safer replication?

This paper traces this choice to a labor-market origin. Existing work on what encourages entrepreneurial risk-taking focuses on insurance to entrepreneurs themselves, such as bankruptcy protection and unemployment benefits targeted at entrepreneurs. But entrepreneurs are not the only ones exposed. When an experiment fails, workers lose their jobs, and they must be compensated for that risk 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. Thus, we put workers at the center of entrepreneurial risk-taking, characterizing this unemployment-safety channel in a structural model and testing it with Danish administrative data and a novel randomized survey experiment linked to those same registers.

First, 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 loss incurred when they are returned to unemployment. Safer unemployment conditions reduce this 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, since job loss is less costly when the unemployed can find another job easily. In the quantitative analysis, we trace how changes in job-finding rates propagate into firm entry, experimentation, and aggregate productivity. Our main experiment raises the job-finding rate through matching efficiency, a reduced-form stand-in for the institutions that ease re-employment: higher matching efficiency raises the equilibrium job-finding rate, reduces the loss from job loss, and thereby lowers wage differentials between experimenting and non-experimenting firms.

The resulting shift in relative wages encourages a greater share of entrants to pursue risky experimentation, further raising aggregate productivity. Overall, a 12-percentage-point increase in the quarterly job-finding rate raises the share of entrants choosing risky experimentation by 6 percentage points, which, in turn, increases aggregate productivity by approximately 1%. Decomposing this productivity 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 exercise, we take the mechanism to the data and test 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 safer firms. Because experimentation is not directly observable, we exploit its life-cycle structure and examine the young–mature wage differential. In the model, a failed experiment closes the firm and puts its workers out of work, and this happens while the firm is still young. Workers at young firms therefore expect shorter matches than workers at mature firms, and the difference comes from experimentation. The young–mature differential responds to job-finding rates for the same reason the risky–safe differential does, though less sharply, since not every young firm experiments.¹ We test this prediction using geographic variation in job-finding rates across Danish commuting zones, drawing on matched employer–employee data for 2008–2022 that cover roughly 14 million worker-year observations.

We estimate wage equations with worker fixed effects, augmented, in increasingly demanding specifications, by industry, industry×year, commuting-zone, and

¹Both premises, that experimentation is concentrated among young firms, and that young firms expose workers to more job loss, have support outside the model. Patents capture only one form of experimentation, but the age pattern is the same: young firms’ patents are more novel and highly cited (Ewens and Marx, 2024), and exploratory activity is concentrated among small and young firms (Akçigit and Kerr, 2010, 2018). Exit hazards also decline steeply with firm age (Haltiwanger et al., 2013), so workers at young firms face a materially higher chance of losing their jobs.

firm fixed effects, and interact a young-firm indicator with local job-finding rates. The coefficient on this interaction asks whether the young–mature wage differential falls as job-finding conditions improve. Identification comes from both cross-market variation and, in the most demanding specifications, from within-firm changes over the firm life cycle and differences in the local conditions faced by workers employed by the same firm. Consistent with the mechanism, the interaction is negative, statistically significant at the 1% level, and stable across specifications.

We then use the estimated wage equations to construct predicted young–mature wage differentials by commuting zone and year and relate them to the local share of firms that are young. The estimated elasticity is negative and broadly in line with the elasticity generated by the calibrated model. While this cross-market correlation does not causally identify the elasticity of firm entry, it provides an untargeted check of the model’s entry-composition margin using an observable empirical counterpart to experimentation.

The negative relationship between local job-finding rates and the young–mature wage differential provides equilibrium evidence consistent with the model. The principal threat to interpreting this association as reflecting the model’s worker-side mechanism is an omitted local shock that both changes job-finding conditions and shifts young firms’ labor demand relative to mature firms’ labor demand. Existing evidence shows that employment at young firms is more cyclical than employment at mature firms and that young-firm job creation responds especially strongly to local economic conditions (Fort et al., 2013; Pugsley and Şahin, 2019). Financial constraints may amplify this differential sensitivity to adverse shocks (Siemer, 2019). Consequently, demand-side forces of this kind would tend to produce a positive interaction between firm youth and the job-finding rate, attenuating rather than generating our negative estimate. Following the logic of Mian and Sufi (2014), we nevertheless probe this concern by restricting the sample to manufacturing firms, whose product demand is on average less closely tied to their local market; the estimated interaction remains negative and similar in magnitude. This check narrows the scope for a local-demand interpretation but does not make local job-finding rates exogenous. The register test therefore remains indirect because firm age only proxies for experimentation exposure, and correlational because job-finding rates are not randomly assigned.

We therefore complement the evidence from administrative data with a randomized survey experiment that represents experimentation risk directly. The experiment

elicits the wage differential workers require to accept employment at a higher-failure-risk young firm and randomly varies the expected duration of unemployment following job loss. 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 pre-registered 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 is 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 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 2.8 percentage points following a doubling, within one standard error of the survey estimate. The experiment therefore provides direct causal support for the worker-side mechanism and shows that the model’s untargeted wage-premium sensitivity is quantitatively consistent with the experimental estimates.

²This 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.

This comparison is the paper’s methodological contribution: it disciplines the model where its general-equilibrium predictions originate, in the partial-equilibrium decision rules of its agents. Quantitative models of firm dynamics are usually calibrated to equilibrium outcomes in microdata, which reflect these rules only jointly with firms’ responses and equilibrium feedback. Survey experiments measure the rules more directly: they identify how beliefs pass through into decisions, either by tracking actions after randomized information treatments or, as in our survey, by eliciting choices under randomly assigned hypothetical scenarios (Coibion et al., 2020, 2022; Coibion and Gorodnichenko, 2026a,b). Taking stock of this agenda in their 2025 Schumpeter Lecture, Coibion and Gorodnichenko (2026b) argue that these methods, having brought causal evidence to a question at the core of macroeconomic models, could allow macroeconomists to “validate and quantify some of the most fundamental mechanisms at work in our models,” while noting how rarely the resulting partial-equilibrium estimates have been mapped into general-equilibrium models. Administering the same questionnaire to the model’s agents provides this mapping: the in-model experiment is the partial-equilibrium counterpart of the survey estimate, which the model then translates into the equilibrium responses of entry, experimentation, and aggregate productivity.

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, not just entrepreneurs, bear the downside risk of experimentation, and the compensation they require affects entrants’ incentives to choose risky, high-upside business models. Notably, Kim (2025) embeds learning about firm type into a directed-search model and shows how the young–mature wage differential depends on firm productivity,

providing a microfoundation for the premium itself. We differ in two respects. First, firm types are given in her setting, whereas entrants in our model choose whether to experiment, so the composition of young firms is itself an equilibrium object. Second, our question primarily concerns not the level of the premium but how it responds to labor-market conditions: because the differential is governed by the cost of job loss, it moves with the job-finding rate, and this comparative static exercise is what we take to the administrative data and survey analysis.

Our paper is also related to work showing that unemployment insurance can affect productivity by changing the composition of jobs. [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.³ [Van Doornik et al. \(2022\)](#) show that a Brazilian reform tightening UI eligibility raised the compensating differential riskier firms must pay and reduced new-business formation. [Clymo et al. \(2026\)](#) study a job ladder in which jobs differ in productivity and separation risk, and show that more generous unemployment insurance encourages risk-averse, imperfectly insured workers to move to riskier but more productive employers. We contribute to this literature in two respects. First, benefit generosity and re-employment prospects are distinct components of the cost of job loss; these papers vary the former, whereas our evidence identifies the latter. Second, we bring the mechanism into a quantitative model of multi-worker firm dynamics in which the productivity distribution is endogenous, rather than one in which workers are allocated across a given distribution of jobs.

Our paper also contributes to the large literature on the implications of firm heterogeneity for aggregate productivity in the presence of labor-market frictions. 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 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 perspective, our paper emphasizes

³The source of the compensating differential also differs. In [Acemoglu and Shimer \(1999\)](#), separation rates are common across jobs, so unemployment risk arises from the queue a worker joins while searching. In our model, risky young firms expose employed workers to a shorter expected match duration and hence to a higher probability of returning to unemployment.

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 shift entry toward high-upside experimentation, raising the equilibrium share of highly productive firms. 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.

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 that these mechanisms all insure the founder. We show that insuring the employee works through the same channel: it lowers the wage compensation required to staff a risky venture, and therefore shapes what kind of business is founded in the first place.

Finally, on the methodological side, the paper relates to a growing body of work that connects survey evidence with economic models. Strategic survey questions elicit stated choices designed to identify a model’s preference parameters ([Ameriks et al., 2020](#)), vignette studies of macroeconomic beliefs use standard models as a benchmark for respondents’ answers ([Andre et al., 2022](#)), and randomized treatments in firm surveys have been used to quantify the productivity losses from misallocation induced by dispersed inflation expectations ([Ropele et al., 2024](#)). Closest to our setting, [Clymo et al. \(2026\)](#) combine a representative survey eliciting workers’ wage–safety indifference curves with a general-equilibrium job-ladder model. We complement this work by randomizing the cost of job loss and replicating the experiment inside the model, so that the survey disciplines how the model’s decision rules respond to that cost—the margin through which its aggregate results operate.

2 The model

We build on the foundational 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.

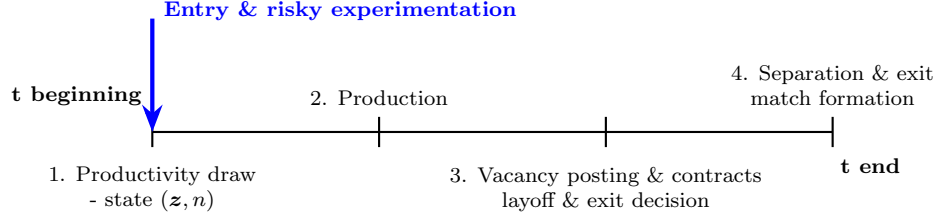
Because entrants are ex ante identical, all firms would choose the same business model absent additional heterogeneity. To generate dispersion in entry choices and allow safe and experimenting firms to coexist in equilibrium, we introduce idiosyncratic taste shocks for the safe business model, in the 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 produc-

Figure 1: Timing



tivity 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. The function $\lambda(m)$ is increasing in m with $\lambda(0) = 0$: filling vacancies faster requires attracting a longer queue of applicants per vacancy. Conditional on searching in that submarket, a worker's matching probability is $m/\lambda(m)$.

2.3 Timing

The timing within each period 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, incumbent firms that have not yet matured do so with probability φ . New entrants face the maturity transition beginning in the following period. For safe firms, becoming mature leaves permanent productivity unchanged at z_e ; for risky young firms, it 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 $\mathbf{z} = (z_p, z_i)$, 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

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

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 $E^j(\mathbf{z}, n; \mathcal{C}_\iota)$ 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 $\mathbf{z}$ and n workers. The operator $\mathbb{E}_{z_\iota}$ 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 $E^j(\mathbf{z}', n'; \mathcal{C}_\iota)$ 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 $\mathbb{E}_{z_\iota} E^j(\mathbf{z}', n'; \mathcal{C}_\iota)$; otherwise she remains unemployed with continuation value U' .

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

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

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 $\mathbb{E}_{z_\iota} E^j(\mathbf{z}', n'; \mathcal{C}_\iota)$ —more workers queue for it, which increases the queue length and lowers the worker's matching probability.

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

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

where $\mathbb{E}_{(\mathbf{z}', j')}$ denotes the expectation over the firm's next-period productivity $\mathbf{z}'$ and maturity type j' and $p_{\varsigma_\iota} = (1 - s_\iota)(1 - \delta_\iota)$ 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_t} , 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 $V_a^j[\{\mathcal{C}_\tau\}_{\tau=0}^{a-1}, \{n_\tau\}_{\tau=0}^{a-1}, (z_p, z_i)]$ denote the value at the beginning of the period. The firm has productivity $\mathbf{z} = (z_p, z_i)$ and a workforce n composed of previous hiring cohorts $\{n_\tau\}_{\tau=0}^{a-1}$, each associated with a contract $\mathcal{C}_\tau$. Safe and risky mature firms solve the same optimization problem conditional on their current state, since both operate with known permanent productivity. For safe firms, this permanent productivity is fixed at z_e ; for risky mature firms, it is the realized draw z_m from prior experimentation. Accordingly, the same value-function expression applies to both types, with $z_p = z_e$ for safe firms and $z_p = z_m$ for risky mature firms.

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

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

subject to

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

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

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

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 $s_{\tau}(z_p, z_i) \geq s_0$. 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:

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

subject to

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

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

$$\rho = \beta \frac{m}{\lambda(m)} (1 - \delta) [\mathbb{E}_{z'_i|z_i} \{(1 - \varphi) E^{ry}((z_p, z'_i), n'; \mathcal{C}_a) + \varphi \mathbb{E}_{z_m} E^{rm}((z_m, z'_i), n'; \mathcal{C}_a)\} - U] \quad \text{if } m > 0.$$

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, risky and safe. Risky entrants experiment by pursuing a new or less proven business idea. Safe entrants replicate an established activity in the sense of [Hurst and Pugsley \(2011\)](#). They do not introduce new products, services, or markets, and they do not intend to grow. Risky entrants therefore face greater downside risk but also the possibility of substantially better outcomes, whereas safe entrants face more predictable outcomes. Our notion of experimentation is thus broader than innovation narrowly defined, since it is not restricted to high-tech sectors or formal R&D. 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:

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

where $\mathbb{E}_\epsilon$ denotes the expectation over the idiosyncratic taste shocks ϵ .

We further assume that the taste shocks ϵ follow a logistic distribution with mean zero and scale parameter σ_σ . Under this assumption, the value of entry simplifies to:

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

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

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

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

Finally, 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_t . Iterating the employment value (3) forward yields

$$E^j(\mathbf{z}, n; \mathcal{C}_t) - U = A_t(\mathbf{z}, n) [w_t - (1 - \beta)U], \quad (9)$$

where $A_t(\mathbf{z}, n) = 1 + \beta p_{\zeta_t}(\mathbf{z}, n) \mathbb{E}_{z_t} A_t(\mathbf{z}', n')$ is the expected discounted duration of the match under contract $\mathcal{C}_t$.

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

$$w_t = b + \rho + \frac{1}{\beta(1 - \delta_t)} \frac{\lambda(m_t)}{m_t} \frac{\rho}{\mathbb{E}_{z_t} A'_t}. \quad (10)$$

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, $\lambda(m_t)/m_t$. Our mechanism instead operates through expected match duration, $\mathbb{E}_{z_t} A'_t$: 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. As shown by [Kaas and Kircher \(2015\)](#), this implies that 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

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

The first term is the capital loss associated with being returned to unemployment.

Indeed, the worker-attraction condition implies

$$\frac{\rho}{\beta} \frac{\lambda(m)}{m} = (1 - \delta_i) [\mathbb{E}_{z_i} E^j(\mathbf{z}', n'; \mathcal{C}_i) - U].$$

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 $w_{ry} > w_s$. The shorter expected durations at risky young firms hold in our calibrated equilibrium.

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 re-employment 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. [Appendix A.4](#) establishes that this result continues to hold when entrants

choose between business models before posting contracts.⁴ 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 matching function takes the CES form used by Kaas and Kircher (2015), $\lambda(m) = \left(\frac{m^{-r}-1}{k}\right)^{-1/r}$. The vacancy cost function is $c(v, n) = \frac{\chi_0}{1+\chi_1} \left(\frac{v}{1+n}\right)^{\chi_1} v$.⁵

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

⁴Conditional on the entry choice, the business model indexes an exogenous productivity process, so the hiring, layoff, and exit margins are efficient exactly as in Kaas and Kircher (2015), and the choice is made before any contract is posted, so it does not erode the firm's commitments. Sorting across business models is efficient because each entrant's private value equals the corresponding social value, and because the taste shock is a payoff the planner also counts; the planner's free-entry condition is therefore the same logsum as in the decentralized equilibrium. The formal proof is in Appendix A.4.

⁵The denominator in the vacancy cost function is $n+1$, not n , following Kaas and Kircher (2015), so that entrants, who have zero existing workers, do not face an infinite vacancy creation cost.

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 scales the taste shocks that generate dispersion in entry choices and thereby determines, for a given excess return to experimentation, the equilibrium composition of entrants. In the baseline, we calibrate σ_σ by targeting a risky-entrant 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 equilibrium excess return $\Delta\mathcal{E} \equiv \mathcal{E}^{ry} - \mathcal{E}^s$, σ_σ is recovered as

$$\sigma_\sigma = \frac{\Delta\mathcal{E}}{\log(P(R)/(1 - P(R)))}. \quad (12)$$

Intuitively, the larger the pecuniary excess return to experimentation, the greater the dispersion in taste shocks needed to keep the experimentation share at the 0.6 target. Absent taste shocks, any positive excess return would lead all entrants to experiment. Keeping 40 percent of entrants in the safe model therefore requires nonpecuniary preferences strong enough to offset the excess return, and the larger the return, the stronger they must be.

Because σ_σ is calibrated to the level of the experimentation share, the response of that share to wages is not targeted and provides a test of the model. We compare the model's elasticity of the experimentation share with respect to the risky–safe wage differential with its empirical counterpart. Because experimentation is not observed, we use its life-cycle structure. Greater experimentation raises failure when uncertainty is resolved, lowers survival into maturity, and so raises the equilibrium share of young firms; the elasticity of the young-firm share with respect to the young–mature wage differential is therefore the observable counterpart of the experimentation elasticity. Section 5.2.2 estimates it from the register data. A one-percentage-point rise in young firms' wages relative to mature firms lowers the share of young firms by 0.9 percentage points; the calibrated model implies 1.3.

4 Model experiments

In this section, we study the effects of higher matching efficiency, which raises workers' equilibrium job-finding rate. 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 1: Parameters and targeted moments

Parameter		Value	Moment	Model	Data
A. Externally set					
β	Discount factor	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 CES parameter	0.944	Petrongolo and Pissarides (2001)		
φ	Prob. of becoming 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		

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.⁶ Because risky entrants have 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 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

⁶The job-finding rate in Table 2 is the average of workers’ job-finding rates $m_i/\lambda(m_i)$ across submarkets, weighted by job seekers. The $f = 0.48$ used to recover r and k in Section 3 is the job-finding rate at queue length $\bar{\lambda} = 1$. Because queue lengths differ across firms and job seekers are concentrated where queues are longer, the average (0.44) lies slightly below f .

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 wages (safe and risky), young firm wage, mature firm wage, and the entrants mass. For the job-finding rate, share of experimentation, young firm share, and young firm employment share, the unit is percentage point (p.p.) change.

employment.

The response of the entry composition to wages follows from a two-step chain rule. Let $dg \equiv d \ln w^y - d \ln w^s$ denote a change in the relative entrant wage. Then

$$\frac{dP(R)}{dg} = \frac{d \ln \Delta \mathcal{E}}{dg} \times \frac{dP(R)}{d \ln \Delta \mathcal{E}}.$$

The first factor measures how the relative value of experimentation responds to a change in relative entrant wages. The second measures how a given change in that relative value translates into the share of entrants who experiment.

The first factor reflects how wage costs enter the entry values, and is therefore a function of the calibrated productivity process and exit rates. The second factor is determined by the logistic form of equation (8). Using the calibration of σ_σ (Eq. (12)), it depends only on $P(R)$:

$$\frac{dP(R)}{d \ln \Delta \mathcal{E}} = P(R) [1 - P(R)] \log \frac{P(R)}{1 - P(R)}.$$

This factor equals 0.10 at the calibrated share $P(R) = 0.6$. Although the translation from values into choices relies on the logistic distribution of taste shocks, this factor leaves no room to amplify the entry response. Once σ_σ is set to match $P(R)$, it has no remaining degree of freedom, and its value is nearly independent of the distributional assumption: for any symmetric, mean-zero distribution of taste shocks, it

is approximately $P(R) - 1/2$ to a first order.⁷ Alternative assumptions on the distribution of taste shocks therefore cannot amplify the entry response, which, given the targeted share, depends on the first factor, an outcome of the calibration to the targeted moments.

What matters is how strongly the relative return to experimentation depends on the wage differential. In the calibrated model, this dependence is strong because the return is small. Experimentation involves a trade-off between its high upside potential on the one hand and the higher exit rates and the compensating premium that come with it on the other, and the two largely offset each other. A small change in wage costs is therefore large relative to $\Delta\mathcal{E}$: in Table 2, a 0.72 log-point fall in the relative entrant wage is accompanied by a 68 percent rise in $\Delta\mathcal{E}$. This mirrors the role of a small fundamental surplus in the response of vacancy creation in matching models (Ljungqvist and Sargent, 2017).

Each component of this trade-off is disciplined by the data. The upside and the exit rates follow from the productivity and exit processes, which match the age gradient in exit hazards and the size distribution of mature firms in Table 1. The premium reflects the price that workers require for bearing separation risk. Risky entrants pay a premium of 0.95 percent per percentage point of additional separation risk, similar in magnitude to, and if anything smaller than, the 1.63 percent per percentage point of additional unemployment risk estimated by Clymo et al. (2026). A small excess return is also consistent with the evidence that business ownership earns little or no premium for its risk (Moskowitz and Vissing-Jørgensen, 2002; Hamilton, 2000), even in its riskiest forms, venture-backed startups and independent invention (Hall and Woodward, 2010; Åstebro, 2003).

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:

⁷Let F denote the distribution of taste shocks with density f , and $x \equiv F^{-1}(P(R))$. Calibrating σ_σ to $P(R)$ gives $dP(R)/d\ln \Delta\mathcal{E} = f(x)x$, and $F(x) \approx 1/2 + f(0)x$ implies $f(x)x \approx P(R) - 1/2$. At $P(R) = 0.6$, the factor equals 0.097 under the logistic distribution, 0.098 under the normal, and 0.094 under the Cauchy.

$$\begin{aligned}
TFP = & \underbrace{M^{1-\alpha}}_{\text{Total mass}} \times \underbrace{\left(\frac{1}{M^{1-\alpha}} \left(\int z_k^{\frac{1}{1-\alpha}} dk \right)^{1-\alpha} \right)}_{\text{Productivity distribution}} \\
& \times \underbrace{\left(\frac{1}{\left(\int z_k^{\frac{1}{1-\alpha}} dk \right)^{1-\alpha}} \left(\frac{\int z_k^{\frac{1}{1-\alpha}} (n_k/y_k)^{\frac{\alpha}{1-\alpha}} dk}{\left(\int z_k^{\frac{1}{1-\alpha}} (n_k/y_k)^{\frac{1}{1-\alpha}} dk \right)^\alpha} \right) \right)}_{\text{Allocative efficiency}}, \tag{13}
\end{aligned}$$

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).⁸

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 1.05%. The primary driver of this gain is an upward shift in the firm productivity distribution, which contributes approximately 1.18% to aggregate productivity. As lower hiring costs reduce the relative wage premium for risky entrants, increased experimentation serves as the central force behind this compositional improvement. 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

⁸Because the equilibrium in our directed-search environment is socially efficient, this dispersion reflects the efficient distribution of labor given hiring frictions, rather than suboptimal misallocation. A reduction in this dispersion indicates that lower matching frictions allow the economy to operate closer to the frictionless benchmark, raising aggregate output for a given level of employment.

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), affects 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.

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.

We have used the job-finding rate as the measure of workers’ safety in unemployment, as this is the object we bring to the analysis with administrative data and the survey experiment. In principle, unemployment benefits, which are one component of safety in unemployment, work in the same way as the job-finding rate. Appendix A.5 shows that higher unemployment benefits reduce the wage differential between risky and safe young firms and the differential between young and mature firms, which increases the share of experimenters and aggregate productivity.

5 Empirical analysis

The register analysis asks whether the model’s equilibrium wage implication is present in administrative data. Through the worker-attraction constraint, better re-employment prospects reduce the compensation required to attract workers to firms with greater separation risk. The model therefore predicts that wages at young firms fall relative to those at mature firms when local job-finding conditions improve. Because experimentation is not observed in the administrative data, we exploit its life-cycle structure. Firms whose experiments fail exit while young, displacing their workers, whereas this uncertainty is resolved among firms that survive to maturity. Firm age therefore serves as a proxy for exposure to experimentation-related job loss. Because only some young firms experiment, the young–mature comparison is, within the model, an attenuated counterpart to the risky–safe differential.

We assign each worker the job-finding rate in their commuting zone, which we interpret as the local labor market governing their outside option. Directed search is

understood as operating across the contracts offered in that local market. A firm may recruit workers residing in several commuting zones; in the model-to-data mapping, it is then treated as recruiting in several local markets whose workers face different outside options. Cross-area differences in job-finding conditions are represented in the model by differences in matching efficiency, interpreted as a reduced-form parameter summarizing local forces that make it easier or harder for unemployed workers to find jobs.

Because local job-finding rates are not randomly assigned, the register estimates document a conditional equilibrium association rather than causally identify the worker-side mechanism. The survey experiment in Section 6 provides that sharper test by holding the difference in firm-closure risk fixed and randomly varying expected unemployment duration following job loss.

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 2022.

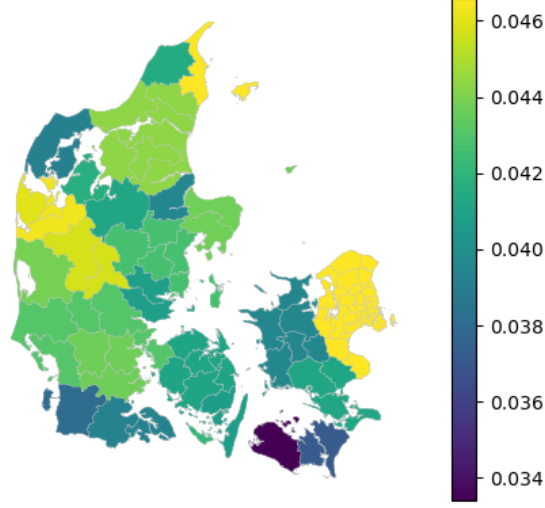
Population Registry: *Befolkningen* (BEF) is an individual-level dataset that includes information such as date of birth, gender, address, civil status, and more. We use the residential address data to map workers to their commuting zones, utilizing a mapping provided by Statistics Denmark (DST), which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

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

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

We construct monthly transition rates from non-employment to employment as a proxy for job-finding rates. A worker is classified as non-employed if they do not appear in the BFL registry in a given month. By merging the employment and

Figure 2: Job finding rate by commuting zone



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 job-finding rates into yearly averages for each commuting zone. Figure 2 illustrates the geographic variation in annual job-finding rates across commuting zones. The map reveals substantial heterogeneity across areas: some commuting zones consistently exhibit markedly higher job-finding rates than others. This variation is largely persistent over time, suggesting that it reflects relatively stable differences in local economic conditions rather than transitory fluctuations.⁹

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 wage measurement, 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

⁹Ranking commuting zones by their job-finding rate within each year (so that aggregate fluctuations are removed by construction), the rank correlation between years t and $t + k$ is 0.80 for $k = 1$ and 0.43 for $k = 10$, implying a half-life of roughly eight years. Commuting zones with high job-finding rates in a given year thus tend to remain high-rate commuting zones a decade later.

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 population and education registries, including age 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 14 million worker-year observations over 2008–2022. This includes approximately 2.4 million unique workers and 180,000 unique firms.

5.2 Young-firm relative wages and job-finding rates

5.2.1 Empirical strategy

Firm age is an imperfect but empirically meaningful proxy for exposure to experimentation displacement risk. Novel activity is concentrated among young firms: patents filed in a firm’s first three years are markedly more original and more heavily cited than those filed later (Ewens and Marx, 2024), and exploratory innovation is tilted toward small and young producers (Akcigit and Kerr, 2010, 2018). Displacement risk follows the same age profile: in our sample, the annual exit hazard falls from 16.5% at age three to 10.8% at age ten, consistent with the steep age gradient documented by Haltiwanger et al. (2013).¹⁰ We provide direct evidence on experimentation displacement risk in Section 6.

We estimate variants of the following regression:

$$\ln w_{it} = \beta X_{it} + \gamma_1 Y_{J(i,t)} + \gamma_2 f_{M(i,t)} + \delta (Y_{J(i,t)} \times f_{M(i,t)}) + \epsilon_{it}, \quad (14)$$

where w_{it} denotes the real hourly wage of worker i in year t , and X_{it} collects the worker controls and fixed effects included in each specification. The worker is employed by firm $j = J(i, t)$ and resides in commuting zone $m = M(i, t)$. The indicator $Y_{J(i,t)}$ equals one when the employing firm is young, defined as less than three years old, and zero when it is mature. The variable $f_{M(i,t)}$ is the job-finding rate from non-employment in the worker’s commuting zone. We standardize the job-finding rate by

¹⁰This age gradient can also reflect mechanisms other than experimentation, such as passive learning about firm type (Jovanovic, 1982) or fixed costs interacting with small scale (Clementi and Palazzo, 2016).

demeaning it and dividing it by its standard deviation.

Following Babina et al. (2019), the time-varying worker controls include log years of education and a cubic in log age, normalized by 40, together with interactions between the age polynomial and log education. Because the job-finding rate is demeaned, γ_1 measures the young–mature wage differential at average local job-finding conditions. The coefficient γ_2 captures the association between job-finding conditions and wages at mature firms, the omitted category. Our coefficient of interest is δ , which measures how the young–mature wage differential changes following a one-standard-deviation increase in the local job-finding rate. The model predicts $\delta < 0$.

The interaction coefficient is estimated from variation across commuting zones and over time in the wages paid by young relative to mature firms, conditional on the fixed effects included in each specification. When firm fixed effects are included, all between-firm wage differences are absorbed. The interaction is then identified solely from within-firm variation: changes in the relationship between workers’ local job-finding conditions and wages as firms move from young to mature status and, for firms employing workers from several commuting zones, differences in the local conditions faced by their workers.

Interpreting a negative δ as evidence for the unemployment-safety mechanism requires an exclusion restriction: conditional on the included controls, changes in local job-finding rates must not be accompanied by omitted shocks that directly change young firms’ labor demand relative to mature firms’ labor demand. This does not require firms’ labor demand to remain fixed. Endogenous hiring and wage responses to workers’ outside options are part of the equilibrium mechanism. The restriction instead rules out direct age-specific demand shifts correlated with local job-finding conditions.

This concern is empirically relevant. Previous research finds that employment and job creation at young firms respond more strongly than at mature firms to local demand and cyclical shocks (Fort et al., 2013; Pugsley and Şahin, 2019). Employment at young firms is also particularly sensitive to financial constraints (Siemer, 2019). When local economic conditions improve, labor demand is likely to rise more at young firms than at mature firms. If these demand-side forces also raise local job-finding rates, they tend to increase wages at young firms relative to mature firms when job-finding is high. They would therefore generate a *positive* interaction between firm youth and the job-finding rate, working against, rather than producing, the negative

interaction implied by the unemployment-safety mechanism.

Other unobserved shocks could nevertheless affect relative labor demand differently. Because job-finding rates are not randomly assigned, we therefore interpret δ as an equilibrium conditional correlation rather than as a causal estimate. The survey experiment in Section 6 provides the causal evidence on the worker-side mechanism.

5.2.2 Results

Table 4 reports the wage regressions. All specifications include worker fixed effects, so the estimates are not driven by permanent differences across workers, including ability, earnings capacity, or stable preferences over job-loss risk that may generate sorting between young and mature firms. Column 1 also includes year fixed effects, which absorb aggregate shocks common to Danish workers and firms. Column 2 adds flexible education-specific age profiles, while column 3 controls for permanent differences in wage levels across industries. Column 4 replaces the separate industry and year effects with industry-by-year fixed effects, thereby absorbing national sector-specific demand, productivity, and wage shocks. Column 5 adds commuting-zone fixed effects, which remove persistent differences in wage levels across local areas that are common to young and mature firms. They do not, however, absorb time-varying local demand shocks, which motivate the manufacturing-firm exercise below. Columns 6 and 7 instead introduce firm fixed effects, with column 7 also including commuting-zone fixed effects. Firm fixed effects absorb permanent differences in firm productivity, wage policies, and amenities. These specifications therefore identify the interaction from changes within firms as they move from young to mature status, together with variation in the local job-finding conditions faced by their workers.

Our central result concerns the interaction between the young-firm indicator and the job-finding rate. The interaction is negative and statistically significant at the 1% level in every specification, as predicted by the model. The estimate is also stable across columns 1–5, ranging from approximately -0.009 to -0.011 . Because the job-finding rate is standardized, a one-standard-deviation improvement in local job-finding conditions lowers wages at young firms relative to mature firms by approximately 0.9–1.1 percentage points. The positive main effect of the job-finding rate, together with the negative interaction, implies that wages at young firms respond less than wages at mature firms when re-employment prospects improve. Standard errors are clustered at the commuting-zone level, the level at which the job-finding

Table 4: Young firm and job-finding rate

Young	-0.0291*** (0.00114)	-0.0288*** (0.00110)	-0.0262*** (0.00109)	-0.0301*** (0.00142)	-0.0301*** (0.00142)	-0.00605*** (0.000915)	-0.00606*** (0.000917)
Job finding rate (JFR)	0.0107*** (0.00231)	0.00794*** (0.00159)	0.00791*** (0.00153)	0.00614*** (0.000961)	0.00546*** (0.000891)	0.00690*** (0.00146)	0.00668*** (0.00149)
Young $\times$ JFR	-0.0107*** (0.00296)	-0.0110*** (0.00310)	-0.0107*** (0.00286)	-0.00912*** (0.00240)	-0.00917*** (0.00242)	-0.00618*** (0.00148)	-0.00620*** (0.00148)
Observations	7730144	7730144	7730143	7730026	7730026	7711419	7711419
R-squared	0.868	0.871	0.872	0.875	0.875	0.895	0.895
Controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Worker FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	No	No	No	No
CZ FE	No	No	No	No	Yes	No	Yes
Firm FE	No	No	No	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	No	No	Yes	Yes
Year x Industry FE	No	No	No	Yes	Yes	No	No

Notes: This table presents the baseline results for wages at young firms relative to mature firms and their interaction with labor market conditions. The sample consists of a matched worker-year panel from 2008 to 2022, with the dependent variable being the log of yearly real hourly wages. The sample is further limited to the working-age population aged 30 to 52. 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 commuting-zone level and reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

rate varies; inference is unchanged under alternative clustering choices.

The coefficient on *Young* is negative: at the mean job-finding rate, young firms pay approximately 2.6–3.0% less than mature firms in columns 1–5 and approximately 0.6% less once firm fixed effects are included. This differs from the positive average young–mature differential in the calibrated model. The model uses firm age solely to capture differences in exposure to experimentation risk and abstracts from other age-related determinants of wage levels. In columns 1–5, persistent differences across young and mature firms in productivity, amenities, financing conditions, and worker–firm matching may therefore contribute to the negative level difference (Babina et al., 2019). Firm fixed effects absorb time-invariant firm-level differences, but the coefficient on *Young* may still reflect systematic changes within firms as they mature, including changes in these determinants. Our empirical prediction concerns not the level of the differential, but its response to job-finding conditions, as captured by the interaction coefficient.¹¹

Relative to the otherwise comparable worker-and-year-fixed-effects specification in column 2, adding firm fixed effects in column 6 reduces the interaction coefficient from -0.0110 to approximately -0.0062 . The estimate nevertheless remains precisely estimated and statistically significant at the 1% level. Adding commuting-zone fixed effects in column 7 has essentially no effect on the estimate. In this preferred firm-fixed-effects specification, a one-standard-deviation increase in the job-finding rate raises mature-firm wages by approximately 0.67%, but young-firm wages by only about 0.05%. Thus, wages at young firms fall relative to mature firms by approximately 0.62 percentage points.

Local-demand robustness. To assess the principal demand-side threat, we re-estimate the specification on manufacturing firms. Manufacturing output is largely tradable, so demand for these firms’ products is less tightly linked to conditions in their own commuting zone. This restriction follows Mian and Sufi (2014), who find that local household demand shocks move nontradable employment while leaving tradable employment largely unaffected. We additionally include industry-by-year fixed effects to absorb common sectoral and external-demand shocks. The interaction between the young-firm indicator and the job-finding rate remains negative and significant; see Table B1. Comparing the last columns of Tables 4 and B1, the estimated

¹¹Consistent with this distinction, the survey experiment holds other job attributes constant and finds a positive baseline premium for employment at the riskier young firm.

interaction is -0.00686 in the manufacturing sample, slightly larger in absolute value than the baseline estimate of -0.0062 . If a firm demand channel were driving the baseline result, restricting the sample to tradable-goods producers should attenuate the estimate rather than leave it unchanged. This exercise does not make local job-finding rates exogenous. But it makes it less plausible that differential exposure to local product demand accounts for our result.

Robustness In Appendix B, we report a series of additional robustness checks. First, instead of defining young firms as those less than three years old, we use a five-year cutoff (Table B2). Second, we replace the level of the job-finding rate with its log transformation, to ensure that a small number of extreme values does not drive the results (Table B3). Third, we drop the age restriction on workers and use the full sample rather than the working-age population (Table B4). Fourth, although our conceptual description of risky experimentation and the corresponding calibration are not exclusively about high-tech activity, we restrict the sample to high-tech industries, which are potentially more important for innovation and growth. Following Hecker (2005), we classify an industry as high-tech if its share of workers in high-tech occupations is more than twice the economy-wide average (Table B5). Finally, we define the employer at the establishment rather than the firm level (Table B6). In all of these specifications, the coefficient on the interaction between the young-firm indicator and the job-finding rate remains negative and statistically significant. The negative association between local job-finding rates and wages at young firms relative to mature firms is therefore robust across these alternative specifications.

Young-firm shares and estimated relative wages We next examine whether the estimated wage of young firms relative to mature firms is related to the share of firms that are young, as predicted by the model. Using the wage regressions above, we construct for each commuting zone m and year t the predicted young–mature log wage differential, denoted by $\hat{\omega}_{mt}$.¹² We then estimate

$$s_{mt}^Y = \eta_t + \theta \times \hat{\omega}_{mt} + \varepsilon_{mt}, \quad (15)$$

where s_{mt}^Y is the share of firms in commuting zone m and year t that are young, defined as less than three years old, and η_t denotes year fixed effects. Since $\hat{\omega}_{mt}$

¹²We use the estimate from the last column of Table 4. Specifically, $\hat{\omega}_{mt} = (-0.0062/0.0042) \times f_{mt} \times 100$, where f_{mt} is the job-finding rate in commuting zone m in year t and 0.0042 is the standard deviation of the job-finding rate. We divide 0.0062 by the standard deviation because the estimate comes from a specification in which the job-finding rate is normalized.

is the predicted log wage of young relative to mature firms, θ measures the semi-elasticity of the young-firm share with respect to young firms' relative wage. The model predicts $\theta < 0$: a lower relative wage reduces the labor cost of risky entry, raises experimentation, and increases the equilibrium share of young firms through entry and subsequent survival. The estimated semi-elasticity is $\hat{\theta} = -0.009$ and is statistically significant at 1 percent, meaning that a 1 percentage point increase in young firms' wages relative to mature firms is associated with a 0.9 percentage point reduction in the share of young firms.¹³ This magnitude is broadly in line with the calibrated model, which implies that a 1 percentage point increase in the young-firm wage premium reduces the share of young firms by 1.3 percentage points ($= 0.78/(0.96 - 1.57)$ from Table 2).

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. The register analysis tests this prediction indirectly by using firm age as an observable proxy for experimentation exposure. To examine the wage compensation required specifically for experimentation risk, and to identify the effect of unemployment conditions 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 therefore 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' endogenous wage-setting, hiring, and entry responses. Its limitation is that experimentation is not observed directly and must be proxied by firm age, while variation in job-finding conditions is not randomly assigned. The survey experiment abstracts from

¹³This evidence is qualitatively consistent with U.S. evidence on young firm activity and job mobility that exploits variation across industries (Kim, 2025).

equilibrium firm responses, but gains both experimental control over the worker-side margin and a direct representation of experimentation risk in the choice environment. It therefore tests more directly whether an increase in the cost of job loss causally raises the compensating wage differential workers require to accept employment at a riskier firm.

6.1 Survey description

Sampling and implementation. We embedded a short research module as an addendum to Danmarks Nationalbank’s *Survey of Consumers’ Expectations* (*Nationalbankens forventningsundersøgelse*), a survey designed to be representative of the Danish population.¹⁴ The survey is fielded monthly and sent to 6,000 Danish residents; 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 via personal identification numbers (CPR), 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 over four consecutive months, from January to April 2026, yielding 2,556 eligible respondents in total.

Survey design and content. To minimize experimenter demand effects, 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 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

¹⁴The survey module was pre-registered in the AEA RCT Registry (Faccini and Kim, 2026).

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 randomized 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 standardize 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 behavior, 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 but

may affect the level of the stated risky–safe wage differential. It does not affect the experimental variation of interest, because the growth narrative is held fixed while expected unemployment duration is randomly assigned.

The vignette varies the respondent’s own expected duration of unemployment following job loss and makes no mention of a change in aggregate labor-market conditions. Interpreting the resulting causal effect as operating through the cost of job loss requires that the assigned duration have no effect on the relative attractiveness of the two jobs beyond its intended effect on the expected cost of unemployment following job loss. If respondents nevertheless interpret the assigned duration as informative about broader labor-market conditions, this is immaterial provided that such conditions do not cause them to infer a change in the relative attributes of the two firms. The wording explicitly confines the differences between the two jobs to Company B’s higher closure risk and qualitative growth upside, both of which are held fixed across treatment arms. Thus, by construction, the assigned unemployment duration does not alter any relative job characteristic.

Table 5 reports summary statistics for the survey responses. Respondents expect an average unemployment duration of 3.9 months and require, on average, a 17.6% wage premium to move from the safe to the risky firm. The corresponding standard deviations are 4.8 months and 18.3 percentage points, indicating substantial heterogeneity across respondents. One might nonetheless wonder whether safety in unemployment matters only for low-skilled workers, who are arguably less relevant for the high-upside experimentation undertaken by young firms. To address this, we restrict the sample to respondents in high-skilled occupations and ask whether their distributions of expected unemployment duration and required wage premium differ. Panel B shows that high-skilled respondents report a very similar subjective unemployment duration to the full sample (3.98 versus 3.93 months). They also require a similar wage premium, on average, to move to the risky firm. Safety in unemployment therefore does not appear to be a channel that operates exclusively through low-skilled workers; it is also relevant for high-skilled workers, who are potentially more important for high-upside risky experimentation.

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 $\Delta \ln D_i \in \{-\ln 2, \ln 2\}$, corre-

Table 5: Summary statistics: survey

<i>Panel A: Full sample</i>	Mean	SD	P10	Median	P90	N
Unemployment duration (months)	3.93	4.84	1.00	3.00	8.00	2556
$\Delta w^{\text{risky-safe}}(\%)$	17.55	18.31	0.00	15.00	40.00	2556
<i>Panel B: High-skill occupation</i>						
Unemployment duration (months)	3.98	3.10	1.00	3.00	8.00	269
$\Delta w^{\text{risky-safe}}(\%)$	19.12	20.58	0.00	20.00	40.00	269

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%. Panel A reports summary statistics for the full sample. Panel B restricts the sample to high-skilled respondents in private non-financial corporations, where high-skilled is defined as a 1-digit DISCO occupation code of 2 (“work that requires the highest level of knowledge within the field in question”). Observations are weighted by the survey weights.

sponding 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. For summary statistics on demographics for both the survey sample and the employed workers, see Table B7.

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

$$z_i = \alpha + \beta_D \Delta \ln D_i + \gamma' \mathbf{X}_i + \varepsilon_i, \quad (16)$$

where $\mathbf{X}_i$ is a vector of control variables. The coefficient β_D is the 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.¹⁵

The 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

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

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 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. 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 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 elasticity is constant across baseline unemployment durations.

Quantitative comparison between model and survey. We next compare the sensitivity of the risky–safe wage premium to expected unemployment duration in the model and the survey. To construct the 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

¹⁵According to the wage equation (10), $z_i \approx 100 \times (w^{\text{risky}} - w^{\text{safe}})/w^{\text{safe}} = 100c_1 D/(c_2 + c_3 D)$, 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*** (0.879)	3.863*** (0.989)	3.710*** (0.934)	3.404*** (0.881)
$(\ln D_i \times \Delta \ln D_i)$		0.401 (0.989)	1.002 (0.896)	1.306 (0.906)
Observations	2556	2556	2556	2556
R-squared	0.0814	0.0421	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.

$w_s(x)$ 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.

For each model worker, we construct the reservation premium

$$z_x(D) = 100 [\ln w_{ry}^*(x, D) - \ln w_s(x)],$$

where D is the worker’s expected unemployment duration. We then double or halve D by halving or doubling the worker’s personal job-finding rate, holding everything else constant. The exact model counterpart of β_D in Equation (16) is the employment-weighted average of $\frac{z_x(2D) - z_x(D/2)}{\ln 2 - \ln(1/2)}$ across workers, with weights given by employment at safe young firms.¹⁶ This model-survey exercise implies that doubling expected unemployment duration raises the required wage premium by 2.85 percentage points.

¹⁶The population counterpart of the OLS coefficient β_D in Equation (16) is $\text{Cov}(x, y)/\text{Var}(x)$, where $x = \Delta \ln D$ and y is the reservation premium. In the model, $x \in \{\ln 2, -\ln 2\}$ with probability 1/2 each; writing $y_+ = z_x(2D)$ and $y_- = z_x(D/2)$, we have $E[x] = 0$, so $\text{Var}(x) = (\ln 2)^2$ and $\text{Cov}(x, y) = \frac{1}{2}(\ln 2)(y_+ - y_-)$, giving a slope of $(y_+ - y_-)/(2 \ln 2)$ for each worker type x . Since the distribution of x is the same across types, pooling yields $\beta_D = \sum_x \omega_x [z_x(2D) - z_x(D/2)] / (2 \ln 2)$, where ω_x is the baseline share of employment at safe young firms accounted for by type x .

Table 7 compares this model prediction with the estimate from the baseline survey specification. Doubling expected unemployment duration raises the required premium by 2.85 percentage points in the model and by 2.30 percentage points in the survey (the first column in Table 6), with a standard error of 0.61. The model prediction is therefore less than one standard error above the survey estimate and lies within its 95% confidence interval of $[1.11, 3.50]$. The comparison is direct, as we administer the same survey experiment to real respondents and model workers. The model’s sensitivity of the compensating wage premium to unemployment duration is therefore quantitatively consistent with the experimental estimate.

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

	Model	Survey
$\beta_D \times \ln(2)$	2.85	2.30
		(0.61)

Notes: This table compares estimates of how the wage premium responds to changes in unemployment duration. The value 2.30 in the “Survey” column is the estimate $3.325 \times \ln 2$ from the first column of Table 6, and the standard error 0.61 is $0.879 \times \ln 2$.

7 Conclusion

This paper proposes a mechanism linking the cost of job loss to productivity through its effect on the relative wages of risky and safe entrants, and hence on firms’ incentives to experiment. 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.

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ONLINE 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 $\Gamma_s(\mathbf{z}, n)$, $\Gamma_{ry}(\mathbf{z}, n)$, and $\Gamma_{rm}(\mathbf{z}, n)$, respectively. The distribution of safe firms, Γ_s , evolves as follows:

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

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 zero workers and an average productivity draw.

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

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

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_{ry} , evolves as:

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

A.2 Labor market clearing

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

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

where u represents the mass of unemployed workers and $\Gamma_s(\mathbf{z}, n)$, $\Gamma_{ry}(\mathbf{z}, n)$, and $\Gamma_{rm}(\mathbf{z}, n)$ 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 in this class of directed-search environments the decentralized equilibrium is efficient, and Appendix A.4 establishes the same result for our extended model: Proposition A.2 shows that the stationary equilibrium allocation solves the planner's problem with multiplier $\mu = \rho$, and Remark 1 shows conversely that any solution of (22)–(24) generates a stationary equilibrium. The planner's allocation can therefore be characterized through the social value representation of a firm's problem, in which the only state variables are productivity and the number of workers.

Let $G^j(\mathbf{z}, n)$ be the social value of a firm with productivity $\mathbf{z}$ and n workers. It satisfies the following Bellman equation:

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

for $j \in \{s, rm\}$. Similarly, for risky young firms,

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

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

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

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

A.4 Efficiency of the decentralized equilibrium

This section proves that the stationary decentralized equilibrium of Section 2 is socially efficient. The argument follows [Kaas and Kircher \(2015\)](#): Lemma A.1 is the stationary version of their Lemma A.4, and Proposition A.2 is the counterpart of their Propositions 3 and 5. Two features of our model require extensions. First, a firm's productivity process depends on its business model and on whether it has matured. We treat the type and the productivity of a firm as a single Markov state. Second, entrants choose a business model subject to taste shocks. We let the planner assign business models to entrants and let the planner value the taste shocks. The planner's expected value of an entrant is then the logsum in (24), and the planner's assignment rule generates the share of risky entrants in (8).

A.4.1 Notation

Firm state. Let $\zeta \equiv (j, \mathbf{z})$ collect a firm's type $j \in \{s, ry, rm\}$ and its productivity $\mathbf{z} = (z_p, z_i)$. Safe and risky young firms have $z_p = z_e$; risky mature firms have $z_p = z_m \in \mathcal{Z}_m$. The set of states is

$$Z \equiv \{(s, z_e, z_i), (ry, z_e, z_i), (rm, z_m, z_i) : z_i \in \mathcal{Z}_i, z_m \in \mathcal{Z}_m\}.$$

We take $\mathcal{Z}_i$ and $\mathcal{Z}_m$ to be finite.¹⁷ The maturity transition, the draw of permanent productivity, and the draw of temporary productivity define a Markov kernel Q on Z :

$$\begin{aligned} Q((s, z_e, z'_i) \mid (s, z_e, z_i)) &= \Pi(z'_i \mid z_i), \\ Q((ry, z_e, z'_i) \mid (ry, z_e, z_i)) &= (1 - \varphi) \Pi(z'_i \mid z_i), \\ Q((rm, z_m, z'_i) \mid (ry, z_e, z_i)) &= \varphi \Pi_R(z_m) \Pi(z'_i \mid z_i), \\ Q((rm, z_m, z'_i) \mid (rm, z_m, z_i)) &= \Pi(z'_i \mid z_i), \end{aligned}$$

and $Q = 0$ otherwise. We write $\mathbb{E}_{\zeta' \mid \zeta}$ for the expectation under Q . For a safe or a risky mature firm, $\mathbb{E}_{\zeta' \mid \zeta}$ is $\mathbb{E}_{z'_i \mid z_i}$ in (4); for a risky young firm, it is $\mathbb{E}_{z'_i \mid z_i} [(1 - \varphi)(\cdot) + \varphi \mathbb{E}_{z_m}(\cdot)]$ in (5). Output $F(\mathbf{z}, n)$ and vacancy costs $c(v, n)$ do not depend on j .

A firm of age a has a history $\zeta^a = (\zeta_0, \dots, \zeta_a)$. Entrants start in one of two states,

$$\zeta_0^s \equiv (s, z_e, \mu_{z_i}) \quad \text{and} \quad \zeta_0^{ry} \equiv (ry, z_e, \mu_{z_i}),$$

with no workers.

Social value of a firm. With this notation, (22) and (23) are the two cases of one equation. Given $\mu \geq 0$, let $G(\cdot; \mu)$ solve

$$\begin{aligned} G(\zeta, n; \mu) &= \max_{\delta, s, m, v} F(\mathbf{z}, n) - bn - \psi_o - \mu[n + \lambda(m)v] - c(v, n) \\ &\quad + \beta(1 - \delta) \mathbb{E}_{\zeta' \mid \zeta} G(\zeta', n'; \mu) \\ \text{s.t.} \quad n' &= (1 - s)n + mv, \quad \delta \in [\delta_0, 1], \quad s \in [s_0, 1], \\ m &\in [0, 1], \quad v \geq 0. \end{aligned} \tag{25}$$

Then $G((j, \mathbf{z}), n; \mu) = G^j(\mathbf{z}, n)$.

Taste shocks. The taste shock ϵ is drawn from the logistic distribution $\Lambda(\epsilon) = [1 + \exp(-\epsilon/\sigma_\sigma)]^{-1}$. For any pair of real numbers (g^s, g^{ry}) ,

$$\int \max\{g^s + \epsilon, g^{ry}\} d\Lambda(\epsilon) = \sigma_\sigma \log \left(\exp\left(\frac{g^s}{\sigma_\sigma}\right) + \exp\left(\frac{g^{ry}}{\sigma_\sigma}\right) \right), \tag{26}$$

and the maximum inside the integral is attained by $g^s + \epsilon$ if and only if $\epsilon \geq g^{ry} - g^s$. The complementary event has probability

$$\Lambda(g^{ry} - g^s) = \frac{\exp((g^{ry} - g^s)/\sigma_\sigma)}{1 + \exp((g^{ry} - g^s)/\sigma_\sigma)}. \tag{27}$$

¹⁷In the numerical solution both are discretized on finite grids. Finiteness is used only in Lemma A.1(a).

Equations (7) and (8) are (26) and (27) evaluated at $(g^s, g^{ry}) = (\mathcal{E}^s, \mathcal{E}^{ry})$.¹⁸

A.4.2 The planner's problem

Time is discrete, $t = 0, 1, 2, \dots$. At $t = 0$ the planner takes as given the masses $\nu_0(\zeta^a)$ and the workforces $n_0(\zeta^a)$ of incumbent firms of age $a \geq 1$. In every period the planner chooses, for every firm of age $a \geq 0$ with history ζ^a , an exit probability $\delta_t(\zeta^a) \in [\delta_0, 1]$, a separation rate $s_t(\zeta^a) \in [s_0, 1]$, vacancies $v_t(\zeta^a) \geq 0$, and a vacancy-filling probability $m_t(\zeta^a) \in [0, 1]$, knowing that filling rate m requires $\lambda(m)$ job seekers per vacancy.¹⁹ Masses and workforces evolve as

$$\nu_{t+1}(\zeta^{a+1}) = [1 - \delta_t(\zeta^a)] Q(\zeta_{a+1}|\zeta_a) \nu_t(\zeta^a), \quad (28)$$

$$n_{t+1}(\zeta^{a+1}) = [1 - s_t(\zeta^a)] n_t(\zeta^a) + m_t(\zeta^a) v_t(\zeta^a). \quad (29)$$

The planner also chooses the mass of entrants $M_{e,t} \geq 0$. Each entrant draws ϵ from Λ , and the planner assigns it a business model according to a rule $\chi_t : \mathbb{R} \rightarrow \{s, ry\}$. An entrant assigned model j becomes a firm in state ζ_0^j with no workers:

$$\begin{aligned} \nu_t(\zeta_0^s) &= M_{e,t} \int \mathbb{1}\{\chi_t(\epsilon) = s\} d\Lambda(\epsilon), & \nu_t(\zeta_0^{ry}) &= M_{e,t} \int \mathbb{1}\{\chi_t(\epsilon) = ry\} d\Lambda(\epsilon), \\ n_t(\zeta_0^s) &= n_t(\zeta_0^{ry}) = 0. \end{aligned} \quad (30)$$

The planner is utilitarian. It counts the nonpecuniary payoff ϵ of an entrant assigned the safe model, and it counts b as the flow value of nonemployment that an employed worker forgoes. Let

$$O_t(\zeta^a) \equiv F(z_a, n_t(\zeta^a)) - b n_t(\zeta^a) - \psi_o - c(v_t(\zeta^a), n_t(\zeta^a)) \quad (31)$$

denote the flow surplus of a firm. The planner's problem is

$$\max \mathcal{W} \equiv \sum_{t \geq 0} \beta^t \left\{ -\psi_e M_{e,t} + M_{e,t} \int \epsilon \mathbb{1}\{\chi_t(\epsilon) = s\} d\Lambda(\epsilon) + \sum_{a \geq 0} \sum_{\zeta^a} \nu_t(\zeta^a) O_t(\zeta^a) \right\} \quad (P)$$

over $(\delta, s, v, m, M_e, \chi)$, subject to (28)–(30) and, for all t , the resource constraint

$$\sum_{a \geq 0} \sum_{\zeta^a} \nu_t(\zeta^a) \left[n_t(\zeta^a) + \lambda(m_t(\zeta^a)) v_t(\zeta^a) \right] \leq 1. \quad (32)$$

¹⁸Write $\Delta \equiv g^{ry} - g^s$. Then $\int \max\{g^s + \epsilon, g^{ry}\} d\Lambda(\epsilon) = g^{ry} + \int_{\Delta}^{\infty} [1 - \Lambda(\epsilon)] d\epsilon = g^{ry} + \sigma_{\sigma} \log(1 + e^{-\Delta/\sigma_{\sigma}})$, which equals the right-hand side of (26).

¹⁹As in [Kaas and Kircher \(2015, footnote 20\)](#), the planner does not discriminate between hiring cohorts within a firm. It has no reason to do so, because output and costs depend on the workforce only through its total.

Constraint (32) states that employed workers plus job seekers cannot exceed the unit mass of workers. Every worker who is not employed, whether or not she is attached to a vacancy, receives b ; the objective omits the constant $b/(1 - \beta)$ that accrues if nobody works. We call $\mathbf{A} \equiv (\nu, n, \delta, s, v, m, M_e, \chi)$ an allocation and say that $\mathbf{A}$ is feasible if it satisfies (28)–(30) and (32).

A.4.3 Social value representation

For an allocation $\mathbf{A}$ and an entrant of date t with initial state ζ_0 , let

$$S_t(\zeta_0; \mathbf{A}) \equiv \sum_{a \geq 0} \beta^a \sum_{\zeta^a | \zeta_0} \left[\prod_{k=0}^{a-1} (1 - \delta_{t+k}(\zeta^k)) Q(\zeta_{k+1} | \zeta_k) \right] \times \left\{ O_{t+a}(\zeta^a) - \mu [n_{t+a}(\zeta^a) + \lambda(m_{t+a}(\zeta^a))v_{t+a}(\zeta^a)] \right\} \quad (33)$$

denote the expected discounted sum of the firm's flow surplus net of the shadow cost of the workers attached to it, where the inner sum runs over histories with the given ζ_0 and the empty product equals one. Define $S_0(\zeta^a; \mathbf{A})$ in the same way for an incumbent of age $a \geq 1$ at $t = 0$, starting from $(\zeta_a, n_0(\zeta^a))$. Grouping the firms in (P) by cohort and using (28) and (30),

$$\begin{aligned} & \sum_{t \geq 0} \beta^t \sum_{a, \zeta^a} \nu_t(\zeta^a) \left\{ O_t(\zeta^a) - \mu [n_t(\zeta^a) + \lambda(m_t(\zeta^a))v_t(\zeta^a)] \right\} \\ &= \sum_{t \geq 0} \beta^t \sum_{j \in \{s, ry\}} \nu_t(\zeta_0^j) S_t(\zeta_0^j; \mathbf{A}) + \sum_{a \geq 1, \zeta^a} \nu_0(\zeta^a) S_0(\zeta^a; \mathbf{A}). \end{aligned} \quad (34)$$

Lemma A.1 Fix $\mu \geq 0$.

(a) Equation (25) has a unique bounded solution $G(\cdot; \mu)$, and $G(\zeta, n; \mu)$ is the supremum of the expected discounted sum of $O - \mu[n + \lambda(m)v]$ over all contingent plans (δ, s, m, v) that satisfy the constraints in (25).

(b) Let $\mathbf{A}$ be a feasible allocation such that

- (i) firm policies attain the social value: $S_t(\zeta_0^j; \mathbf{A}) = G(\zeta_0^j, 0; \mu)$ for all t and $j \in \{s, ry\}$, and $S_0(\zeta^a; \mathbf{A}) = G(\zeta_a, n_0(\zeta^a); \mu)$ for every incumbent;
- (ii) entry is optimal: for all t , $\chi_t(\epsilon) = s$ if and only if $G(\zeta_0^s, 0; \mu) + \epsilon \geq G(\zeta_0^{ry}, 0; \mu)$, and

$$\mathcal{E}_G \equiv \sigma_\sigma \log \left(\exp\left(\frac{G(\zeta_0^s, 0; \mu)}{\sigma_\sigma}\right) + \exp\left(\frac{G(\zeta_0^{ry}, 0; \mu)}{\sigma_\sigma}\right) \right) \leq \psi_e, \quad M_{e,t} \geq 0, \quad (35)$$

with complementary slackness;

(iii) the resource constraint binds whenever $\mu > 0$: for all t ,

$$\mu \left[1 - \sum_{a, \zeta^a} \nu_t(\zeta^a) (n_t(\zeta^a) + \lambda(m_t(\zeta^a))v_t(\zeta^a)) \right] = 0.$$

Then $\mathbf{A}$ solves (P).

Proof. Part (a) is Lemma A.4(a) of [Kaas and Kircher \(2015\)](#). Let $K \equiv \max_{\mathbf{z}, n \geq 0} [F(\mathbf{z}, n) - (b + \mu)n]$, with $\mathbf{z}$ ranging over the finitely many productivities in Z ; K is finite and nonnegative because $F(\mathbf{z}, \cdot)$ is strictly concave with $F(\mathbf{z}, 0) = 0$ and $F_n(\mathbf{z}, n) \rightarrow 0$ as $n \rightarrow \infty$. Since $F(\mathbf{z}, n) - (b + \mu)n \rightarrow -\infty$ as $n \rightarrow \infty$, there is $\bar{n}$ such that

$$F(\mathbf{z}, n) - (b + \mu)n - \psi_o + \frac{\beta K}{1 - \beta} < 0 \quad \text{for all } \mathbf{z} \text{ and all } n \geq \bar{n}.$$

From any state (ζ', n') , the expected discounted sum of $O - \mu[n + \lambda(m)v]$ under any plan is at most $F(\mathbf{z}', n') - (b + \mu)n' - \psi_o + \beta K/(1 - \beta)$, because $-c(v, n)$, $-\mu\lambda(m)v$, and $-\psi_o$ are nonpositive and every later flow is at most K . Hence a plan that sets $n' > \bar{n}$ at a node with $\delta < 1$ has a negative continuation value at that node and is improved by exiting there ($\delta = 1$, $v = 0$), which has a zero continuation value and saves $c(v, n) + \mu\lambda(m)v \geq 0$. Every plan is therefore weakly dominated by a plan with $n' \leq \bar{n}$ at all nodes, and the constraint $n' \leq \bar{n}$ can be added to (25) without loss. (States with $n > \bar{n}$ are never reached in Proposition A.2, where firms enter with no workers and, by the same argument, never hire beyond $\bar{n}$.) The right-hand side of (25) then defines an operator on the space of bounded functions on $Z \times [0, \bar{n}]$ that satisfies Blackwell's sufficient conditions with modulus β . It has a unique bounded fixed point, and by the principle of optimality this fixed point is the supremum of the sequential firm-level problem.

Part (b). Let $\mathbf{A}' = (\nu', n', \delta', s', v', m', M'_e, \chi')$ be any feasible allocation and $\mathcal{W}'$ its value. To keep the display short, write

$$\begin{aligned} \mathcal{R}_t(\mathbf{A}) &\equiv \sum_{a, \zeta^a} \nu_t(\zeta^a) \left[O_t(\zeta^a) - \mu(n_t(\zeta^a) + \lambda(m_t(\zeta^a))v_t(\zeta^a)) \right], \\ \mathcal{I}(\chi, g) &\equiv \int \left(\mathbf{1}\{\chi(\epsilon) = s\} [g^s + \epsilon] + \mathbf{1}\{\chi(\epsilon) = ry\} g^{ry} \right) d\Lambda(\epsilon), \end{aligned}$$

and let $g'_S = (S_t(\zeta_0^s; \mathbf{A}'), S_t(\zeta_0^{ry}; \mathbf{A}'))$ and $g_G = (G(\zeta_0^s, 0; \mu), G(\zeta_0^{ry}, 0; \mu))$. Because

$\mu \geq 0$ and $\mathbf{A}'$ satisfies (32),

$$\begin{aligned}
\mathcal{W}' &\leq \sum_{t \geq 0} \beta^t \left\{ -\psi_e M'_{e,t} + M'_{e,t} \int \epsilon \mathbb{1}\{\chi'_t(\epsilon) = s\} d\Lambda + \mathcal{R}_t(\mathbf{A}') + \mu \right\} \\
&= \sum_{t \geq 0} \beta^t \left\{ M'_{e,t} [-\psi_e + \mathcal{I}(\chi'_t, g'_S)] + \mu \right\} + \sum_{a \geq 1, \zeta^a} \nu_0(\zeta^a) S_0(\zeta^a; \mathbf{A}') \\
&\leq \sum_{t \geq 0} \beta^t \left\{ M'_{e,t} [-\psi_e + \mathcal{I}(\chi'_t, g_G)] + \mu \right\} + \sum_{a \geq 1, \zeta^a} \nu_0(\zeta^a) G(\zeta_a, n_0(\zeta^a); \mu) \\
&\leq \sum_{t \geq 0} \beta^t \left\{ M'_{e,t} [-\psi_e + \mathcal{E}_G] + \mu \right\} + \sum_{a \geq 1, \zeta^a} \nu_0(\zeta^a) G(\zeta_a, n_0(\zeta^a); \mu) \\
&\leq \sum_{t \geq 0} \beta^t \mu + \sum_{a \geq 1, \zeta^a} \nu_0(\zeta^a) G(\zeta_a, n_0(\zeta^a); \mu) \\
&= \sum_{t \geq 0} \beta^t \left\{ M_{e,t} [-\psi_e + \mathcal{E}_G] + \mu \right\} + \sum_{a \geq 1, \zeta^a} \nu_0(\zeta^a) G(\zeta_a, n_0(\zeta^a); \mu) \\
&= \sum_{t \geq 0} \beta^t \left\{ -\psi_e M_{e,t} + M_{e,t} \int \epsilon \mathbb{1}\{\chi_t(\epsilon) = s\} d\Lambda + \mathcal{R}_t(\mathbf{A}) + \mu \right\} \\
&= \mathcal{W} + \sum_{t \geq 0} \beta^t \mu \left[1 - \sum_{a, \zeta^a} \nu_t(\zeta^a) (n_t(\zeta^a) + \lambda(m_t(\zeta^a)) v_t(\zeta^a)) \right] = \mathcal{W}.
\end{aligned}$$

The first equality is (34) applied to $\mathbf{A}'$ together with (30). The second inequality holds because the firm-level plans in $\mathbf{A}'$ are feasible for the problem in (25), so part (a) gives $S_t(\zeta_0; \mathbf{A}') \leq G(\zeta_0, 0; \mu)$ and $S_0(\zeta^a; \mathbf{A}') \leq G(\zeta_a, n_0(\zeta^a); \mu)$. The third inequality replaces the assignment χ'_t by the pointwise maximum over $\{s, ry\}$ and uses (26). The fourth inequality uses (35) and $M'_{e,t} \geq 0$. The next equality uses complementary slackness in (ii): $M_{e,t}[\mathcal{E}_G - \psi_e] = 0$. The following equality holds because, by (ii), the rule χ_t attains the pointwise maximum, so $\mathcal{I}(\chi_t, g_G) = \mathcal{E}_G$, and because (i) and (34) applied to $\mathbf{A}$ turn the social values back into the sum over firms. The last equality is (iii). Hence $\mathcal{W}' \leq \mathcal{W}$. ■

A.4.4 The decentralized economy

Contracts. A contract offered by a firm of age a to the workers it hires in that period is

$$\mathcal{C}_a = (w_a(\zeta^k), p_a(\zeta^k))_{k > a},$$

where $w_a(\zeta^k)$ is the wage paid at age k in history ζ^k to a worker who is still employed at the firm, and $p_a(\zeta^k) \in [0, (1 - s_0)(1 - \delta_0)]$ is the probability that the match survives

into age $k+1$.²⁰ Firms commit to their contracts. At age a , the firm's exit probability δ and its cohort-specific separation rates s_τ must deliver the promised match-survival probabilities to all cohorts $\tau < a$:

$$(1 - s_\tau)(1 - \delta) = p_\tau(\zeta^a), \quad s_\tau \geq s_0, \quad \delta \geq \delta_0. \quad (36)$$

Workers. Let U be the value of unemployment and $E(\mathcal{C}_\tau, \zeta^k)$, $k > \tau$, the value of a worker hired under $\mathcal{C}_\tau$ who is employed at the firm at age k in history ζ^k . Equations (3) and (1)–(2) read

$$E(\mathcal{C}_\tau, \zeta^k) = w_\tau(\zeta^k) + \beta \left\{ p_\tau(\zeta^k) \mathbb{E}_{\zeta_{k+1}|\zeta^k} E(\mathcal{C}_\tau, \zeta^{k+1}) + [1 - p_\tau(\zeta^k)] U \right\}, \quad (37)$$

$$U = b + \rho + \beta U, \quad \rho = \max_{(m, \delta, \mathcal{C}_a)} \beta \frac{m}{\lambda(m)} (1 - \delta) \left[\mathbb{E}_{\zeta_{a+1}|\zeta^a} E(\mathcal{C}_a, \zeta^{a+1}) - U \right], \quad (38)$$

where the maximum in (38) is over the contracts posted in equilibrium, each together with the filling probability m and the exit probability δ of the posting firm.

Firms. The state of a firm of age a is $\Sigma_a \equiv ((\mathcal{C}_\tau)_{\tau < a}, (n_\tau)_{\tau < a}, \zeta^a)$, where n_τ is the workforce of cohort τ . Its problem, (4)–(5) in the notation of this section, is

$$J_a(\Sigma_a) = \max_{\delta, m, v, \mathcal{C}_a} F(\mathbf{z}_a, n) - \sum_{\tau < a} w_\tau(\zeta^a) n_\tau - c(v, n) - \psi_o + \beta(1 - \delta) \mathbb{E}_{\zeta_{a+1}|\zeta^a} J_{a+1}(\Sigma_{a+1}) \quad (39)$$

subject to $n = \sum_{\tau < a} n_\tau$; $m \in [0, 1]$, $v \geq 0$, and $n_{a+} = mv$; (36) and $n_{\tau+} = n_\tau p_\tau(\zeta^a)/(1 - \delta)$ for $\tau < a$ when $\delta < 1$; $\Sigma_{a+1} = ((\mathcal{C}_\tau)_{\tau \leq a}, (n_{\tau+})_{\tau \leq a}, \zeta^{a+1})$; and the worker-attraction constraint

$$\rho = \beta \frac{m}{\lambda(m)} (1 - \delta) \left[\mathbb{E}_{\zeta_{a+1}|\zeta^a} E(\mathcal{C}_a, \zeta^{a+1}) - U \right] \quad \text{if } m > 0. \quad (40)$$

An entrant has state $\Sigma_0 = (\emptyset, \emptyset, \zeta_0^j)$ and value $\mathcal{E}^j \equiv J_0(\emptyset, \emptyset, \zeta_0^j)$, $j \in \{s, ry\}$.

Entry. An entrant with taste shock ϵ chooses the safe model if and only if $\mathcal{E}^s + \epsilon \geq \mathcal{E}^{ry}$. The expected value of entry is $\mathcal{E} = \int \max\{\mathcal{E}^s + \epsilon, \mathcal{E}^{ry}\} d\Lambda(\epsilon)$ as in (6), and free entry requires $\mathcal{E} \leq \psi_e$, $M_e \geq 0$, with complementary slackness. By (26)–(27), $\mathcal{E}$ is the logsum (7) and the share of risky entrants is (8).

²⁰In Section 2 a contract specifies a separation rate s_τ and an exit probability δ_τ . The corresponding match-survival probability is $p_\tau = (1 - s_\tau)(1 - \delta_\tau)$, denoted p_{ς_τ} in (3). Letting contracts depend on the history ζ^k rather than on the current productivity $\mathbf{z}_k$ alone is more general and does not affect the argument.

Definition. A *stationary competitive search equilibrium* is a list

$$\left(\rho, U, E(\cdot), (J_a, \mathcal{C}_a, \delta_a, m_a, v_a, (n_{\tau,a})_{\tau < a})_{a \geq 0}, M_e, \nu \right)$$

such that

- (a) *Firm optimality.* For every a and Σ_a , $J_a(\Sigma_a)$ is the value of (39)–(40), and $(\delta_a, m_a, v_a, \mathcal{C}_a)(\Sigma_a)$ are maximizers.
- (b) *Workforce dynamics.* Cohorts evolve as in the constraints of (39) under the firms' policies.
- (c) *Entry optimality.* Entrants choose business models, and $\mathcal{E} \leq \psi_e$, $M_e \geq 0$ hold with complementary slackness, as in the previous paragraph.
- (d) *Worker optimality.* $(\rho, U, E(\cdot))$ satisfy (37)–(38).
- (e) *Stationary masses.* $\nu(\zeta^{a+1}) = [1 - \delta_a(\zeta^a)] Q(\zeta_{a+1} | \zeta_a) \nu(\zeta^a)$, $\nu(\zeta_0^s) = [1 - P(R)] M_e$, and $\nu(\zeta_0^{ry}) = P(R) M_e$.
- (f) *Resource feasibility.*

$$\sum_{a \geq 0} \sum_{\zeta^a} \nu(\zeta^a) [n_a(\zeta^a) + \lambda(m_a(\zeta^a)) v_a(\zeta^a)] = 1, \quad n_a(\zeta^a) \equiv \sum_{\tau < a} n_{\tau,a}(\zeta^a).$$

Along the equilibrium path, past contracts and cohort sizes are functions of the history, so firm policies are written as functions of ζ^a alone. The distributions Γ_s , Γ_{ry} , and Γ_{rm} of Appendix A.1 are the marginals of ν over histories with current type j , productivity z_a , and workforce $n_a(\zeta^a)$; (18)–(20) restate (e), and (21) restates (f) once the mass of unemployed workers is identified with the job seekers attached to posted vacancies, $u = \sum_{a, \zeta^a} \nu(\zeta^a) \lambda(m_a(\zeta^a)) v_a(\zeta^a)$.

A.4.5 Efficiency

Proposition A.2 *Consider a stationary competitive search equilibrium with positive entry, $M_e > 0$.²¹ Let $\mathbf{A}$ be its allocation: masses ν , workforces $n_a(\zeta^a)$, exit probabilities $\delta_a(\zeta^a)$, vacancies $v_a(\zeta^a)$, filling probabilities $m_a(\zeta^a)$, the entry mass M_e , the*

²¹Any stationary equilibrium with a nondegenerate firm distribution has positive entry, because $\delta_0 > 0$.

assignment rule $\chi(\epsilon) = s$ if and only if $\mathcal{E}^s + \epsilon \geq \mathcal{E}^{ry}$, and the average separation rates

$$s_a(\zeta^a) \equiv 1 - \sum_{\tau < a} [1 - s_{\tau,a}(\zeta^a)] \frac{n_{\tau,a}(\zeta^a)}{n_a(\zeta^a)}.$$

Then **A** solves the planner's problem (P) with initial condition (ν, n) and multiplier $\mu = \rho$. In particular:

- (a) the social value of every firm on the equilibrium path is $G(\zeta, n; \rho)$, so (22)–(23) hold with $\mu = \rho$;
- (b) $\mathcal{E}^j = G^j((z_e, \mu_{z_i}), 0)$ for $j \in \{s, ry\}$, so the free-entry condition $\mathcal{E} = \psi_e$ is (24);
- (c) the planner's assignment of business models is the cutoff rule whose share of risky entrants is (8).

Proof. The proof verifies conditions (i)–(iii) of Lemma A.1(b) with $\mu = \rho$.

Step 1: The firm's problem is a social surplus maximization. For a firm with state Σ_a , define its social value as the sum of its own value and the surpluses of its workers,

$$\mathcal{G}_a(\Sigma_a) \equiv J_a(\Sigma_a) + \sum_{\tau < a} n_\tau [E(\mathcal{C}_\tau, \zeta^a) - U]. \quad (41)$$

By (37) and (38), the surplus of a cohort- τ worker satisfies

$$E(\mathcal{C}_\tau, \zeta^a) - U = w_\tau(\zeta^a) - b - \rho + \beta p_\tau(\zeta^a) \mathbb{E}_{\zeta_{a+1}|\zeta_a} [E(\mathcal{C}_\tau, \zeta^{a+1}) - U]. \quad (42)$$

Substitute (39) and (42) into (41). The wage bill $\sum_{\tau < a} w_\tau(\zeta^a) n_\tau$ cancels, and

$$\begin{aligned} \mathcal{G}_a(\Sigma_a) = \max_{\delta, m, v, \mathcal{C}_a} & \left\{ F(\mathbf{z}_a, n) - (b + \rho)n - c(v, n) - \psi_o + \beta(1 - \delta) \mathbb{E}_{\zeta_{a+1}|\zeta_a} J_{a+1}(\Sigma_{a+1}) \right. \\ & \left. + \beta \sum_{\tau < a} n_\tau p_\tau(\zeta^a) \mathbb{E}_{\zeta_{a+1}|\zeta_a} [E(\mathcal{C}_\tau, \zeta^{a+1}) - U] \right\}. \end{aligned}$$

Use $n_\tau p_\tau(\zeta^a) = (1 - \delta)n_{\tau+}$ for $\tau < a$, and multiply (40) by $\lambda(m)v$ to obtain $\rho\lambda(m)v = \beta(1 - \delta)n_{a+} \mathbb{E}_{\zeta_{a+1}|\zeta_a} [E(\mathcal{C}_a, \zeta^{a+1}) - U]$, where both sides vanish when $m = 0$. Then

$$\begin{aligned} \mathcal{G}_a(\Sigma_a) = \max_{\delta, m, v, \mathcal{C}_a} & \left\{ F(\mathbf{z}_a, n) - bn - \rho[n + \lambda(m)v] - c(v, n) - \psi_o \right. \\ & \left. + \beta(1 - \delta) \mathbb{E}_{\zeta_{a+1}|\zeta_a} \left[J_{a+1}(\Sigma_{a+1}) + \sum_{\tau \leq a} n_{\tau+} (E(\mathcal{C}_\tau, \zeta^{a+1}) - U) \right] \right\} \\ = \max_{\delta, m, v, \mathcal{C}_a} & \left\{ F(\mathbf{z}_a, n) - bn - \rho[n + \lambda(m)v] - c(v, n) - \psi_o \right. \\ & \left. + \beta(1 - \delta) \mathbb{E}_{\zeta_{a+1}|\zeta_a} \mathcal{G}_{a+1}(\Sigma_{a+1}) \right\}, \end{aligned} \quad (43)$$

subject to the constraints of (39). The wages in $\mathcal{C}_a$ have dropped out: given (40), the firm is indifferent among all wage paths that deliver the required expected surplus, and $\mathcal{C}_a$ matters only through the retention probabilities $p_a(\cdot)$ that govern the future workforce.

Equation (43) has the form of (25) with $\mu = \rho$. Two differences remain. The firm's state includes past contracts, whose retention probabilities are fixed, and the firm chooses cohort-specific retention probabilities, whereas the planner chooses one separation rate per firm. Neither difference affects values or policies. Consider an entrant with state ζ_0 , which has no past contracts. Iterating (43) forward, $J_0(\emptyset, \emptyset, \zeta_0) = \mathcal{G}_0(\emptyset, \emptyset, \zeta_0)$ is the supremum of the expected discounted sum of $F(\mathbf{z}, n) - bn - \rho[n + \lambda(m)v] - c(v, n) - \psi_o$ over contingent plans of exit probabilities, vacancies, filling probabilities, and cohort-specific retention probabilities that satisfy $\delta \in [\delta_0, 1]$, $m \in [0, 1]$, $v \geq 0$, and (36). By Lemma A.1(a), $G(\zeta_0, 0; \rho)$ is the supremum of the same objective over plans with a cohort-uniform separation rate $s \in [s_0, 1]$. Both objectives depend on the workforce only through its total, and both feasible sets generate the same set of paths for exit, vacancies, filling probabilities, and total workforce: a cohort-specific plan yields $n' = \sum_{\tau} (1 - s_{\tau})n_{\tau} + mv$ with $1 - s_{\tau} \in [0, 1 - s_0]$ by (36), which the uniform rate $s = 1 - \sum_{\tau} (1 - s_{\tau})n_{\tau}/n \in [s_0, 1]$ reproduces, and a uniform plan is a cohort-specific plan. Hence $J_0(\emptyset, \emptyset, \zeta_0) = G(\zeta_0, 0; \rho)$, and the plan chosen by the entrant firm attains $G(\zeta_0, 0; \rho)$ in the planner's firm-level problem.

Because the firm commits to its contracts and there is no strategic interaction, the plan chosen at entry is carried out. At every later node Σ_a on the equilibrium path, the firm's value $\mathcal{G}_a(\Sigma_a)$ is at least the value of continuing the entry plan, which equals $G(\zeta_a, n_a; \rho)$ by the principle of optimality, and at most $G(\zeta_a, n_a; \rho)$, because every continuation plan that respects the firm's outstanding promises is a cohort-specific plan for the planner's firm-level problem. Hence $\mathcal{G}_a(\Sigma_a) = G(\zeta_a, n_a; \rho)$ on the equilibrium path, and the firm's exit, vacancy, filling, and workforce decisions attain the planner's social value at every node. The same holds for incumbents at $t = 0$, whose past contracts were chosen optimally under the same stationary conditions. This is condition (i) with $\mu = \rho$ and proves part (a). It also gives $\mathcal{E}^j = J_0(\emptyset, \emptyset, \zeta_0^j) = G(\zeta_0^j, 0; \rho) = G^j((z_e, \mu_{z_i}), 0)$ for $j \in \{s, ry\}$, which is part (b).

Step 2: Entry. By part (b), the entrants' rule "safe if and only if $\mathcal{E}^s + \epsilon \geq \mathcal{E}^{ry}$ " is the cutoff rule in condition (ii), the expected value of entry $\mathcal{E}$ in (6) equals $\mathcal{E}_G$ in (35), and the free-entry condition in (c) is the complementary-slackness condition

in (ii). With $M_e > 0$, $\mathcal{E}_G = \psi_e$, which is (24). The share of risky entrants (8) is $\Lambda(G(\zeta_0^{ry}, 0; \rho) - G(\zeta_0^s, 0; \rho))$, the planner's share under the cutoff rule, which is part (c).

Step 3: Resources. Condition (f) states that (32) holds with equality in every period, so condition (iii) holds with $\mu = \rho$.

The allocation $\mathbf{A}$ satisfies (28)–(30) by (b) and (e), because $\int \mathbb{1}\{\chi(\epsilon) = s\} d\Lambda(\epsilon) = 1 - P(R)$, and it satisfies (32) by (f). Lemma A.1(b) with $\mu = \rho$ implies that $\mathbf{A}$ solves (P). ■

Remark 1 (Computation) *The converse of Proposition A.2 also holds, and it is what the computation in Appendix A.3 relies on. Let (G, μ) solve (22)–(24), let the policies of (25) and the cutoff rule $\chi(\epsilon) = s$ if and only if $G(\zeta_0^s, 0; \mu) + \epsilon \geq G(\zeta_0^{ry}, 0; \mu)$ generate the stationary masses ν for an entry mass $M_e > 0$ chosen so that (32) holds with equality (ν is proportional to M_e). By Lemma A.1(b), this allocation solves (P). It is a stationary competitive search equilibrium allocation: set $\rho = \mu$ and $U = (b + \rho)/(1 - \beta)$, and let each firm offer its hires the planner's retention probabilities together with any wage path that satisfies (40), for instance the flat wage (10). Reading (41)–(43) backwards, the firm's problem (39)–(40) is then the problem in (25) with $\mu = \rho$, so the planner's policies are optimal for firms; every posted contract delivers ρ , so (37)–(38) hold; and $\mathcal{E}^j = G(\zeta_0^j, 0; \mu)$, so (c) holds. Together with Proposition A.2, every stationary equilibrium allocation is generated by a solution of (22)–(24) with $\mu = \rho$, and conversely. When (22)–(24) have a unique solution with unique policies, as in our numerical solution, the stationary equilibrium allocation is unique and coincides with the planner's.*

A.5 Model experiments: Unemployment benefit

Table A1: Unemployment Benefit and Wages, Experimentation, and Young Firms

	Baseline	High b ($\times 1.5$)	Δ
Job-Finding Rate	0.44	0.42	-1.69
Entrants Wage (Safe)	3.53×10^{-3}	3.55×10^{-3}	0.59
Entrants Wage (Risky)	3.80×10^{-3}	3.79×10^{-3}	-0.21
Young Firm Wage	3.35×10^{-3}	3.39×10^{-3}	1.16
Mature Firm Wage	3.24×10^{-3}	3.30×10^{-3}	1.68
Share of Experimentation	0.60	0.66	6.34
Entrants Mass	2.11×10^{-3}	2.12×10^{-3}	0.57
Young Firm Share	0.36	0.37	0.79
Young Firm Employment Share	0.17	0.17	0.49

Notes: This table shows how a higher unemployment benefit (higher b) affects wage setting, experimentation, and young firm shares. The parameter b is increased by 50% from 0.001 to 0.0015. The column “High b ” reports results for $b = 0.0015$, and the column Δ shows the difference between “High b ” and the baseline. The unit of Δ is percentage change for entrants wages (safe and risky), young firm wage, mature firm wage, and the entrants mass. For the job-finding rate, share of experimentation, young firm share, and young firm employment share, the unit is percentage point (p.p.) change.

Table A2: TFP Decomposition: Baseline vs. Higher Unemployment Benefit

	Baseline	High b ($\times 1.5$)	Δ
Aggregate Productivity (Y/N^α)	5.51×10^{-3}	5.58×10^{-3}	1.26
Total Mass	0.34	0.34	-0.59
Productivity Distribution	1.91×10^{-2}	1.93×10^{-2}	1.18
Allocative efficiency	0.84	0.85	0.67

Notes: This table shows how a higher unemployment benefit (higher b) affects aggregate productivity and its decomposition. The parameter b is increased by 50% from 0.001 to 0.0015. The column “High b ” reports results for $b = 0.0015$, and the column Δ shows the difference between “High b ” and the baseline. The unit of Δ is percentage change.

B Appendix for empirical analysis

Table B1: Young firm and job-finding rate (manufacturing)

Young	-0.0175*** (0.00204)	-0.0170*** (0.00183)	-0.0172*** (0.00181)	-0.0216*** (0.00224)	-0.0216*** (0.00225)	-0.00319 (0.00198)	-0.00319 (0.00198)
Job finding rate (JFR)	0.0115*** (0.00392)	0.00730*** (0.00202)	0.00705*** (0.00187)	0.00323** (0.00124)	0.00288** (0.00128)	0.00665*** (0.00176)	0.00658*** (0.00183)
Young $\times$ JFR	-0.00918** (0.00358)	-0.00762*** (0.00264)	-0.00814*** (0.00265)	-0.00719*** (0.00245)	-0.00716*** (0.00246)	-0.00689*** (0.00200)	-0.00686*** (0.00201)
Observations	2009655	2009655	2009655	2009589	2009589	2008926	2008926
R-squared	0.894	0.898	0.899	0.903	0.903	0.905	0.906
Controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Worker FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	No	No	No	No
CZ FE	No	No	No	No	Yes	No	Yes
Firm FE	No	No	No	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	No	No	Yes	Yes
Year $\times$ Industry FE	No	No	No	Yes	Yes	No	No

Notes: This table presents the 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 2022, with the dependent variable being the log of yearly real hourly wages. The sample is further limited to the working-age population aged 30 to 52 employed in manufacturing industries. 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 commuting-zone level and reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table B2: Young firm and job-finding rate (5-year cutoff)

Young	-0.0273*** (0.00100)	-0.0272*** (0.000999)	-0.0247*** (0.000937)	-0.0285*** (0.00133)	-0.0285*** (0.000613)	-0.00384*** (0.000612)
Job finding rate (JFR)	0.0112*** (0.00238)	0.00843*** (0.00166)	0.00836*** (0.00161)	0.00658*** (0.00103)	0.00591*** (0.000956)	0.00697*** (0.00144)
Young $\times$ JFR	-0.0103*** (0.00239)	-0.0106*** (0.00259)	-0.0101*** (0.00249)	-0.00841*** (0.00197)	-0.00845*** (0.00199)	-0.00401*** (0.000725)
Observations	7730144	7730144	7730143	7730026	7730026	7711419
R-squared	0.868	0.871	0.872	0.875	0.875	0.895
Controls	No	Yes	Yes	Yes	Yes	Yes
Worker FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	No	No	No
CZ FE	No	No	No	No	Yes	Yes
Firm FE	No	No	No	No	No	Yes
Year FE	Yes	Yes	Yes	No	No	Yes
Year x Industry FE	No	No	No	Yes	Yes	No

Notes: This table presents the 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 2022, with the dependent variable being the log of yearly real hourly wages. The sample is further limited to the working-age population aged 30 to 52. 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 commuting-zone level and reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table B3: Young firm and job-finding rate (log-job-finding rate)

Young	-0.0290*** (0.00113)	-0.0287*** (0.00110)	-0.0262*** (0.00108)	-0.0300*** (0.00141)	-0.0300*** (0.00142)	-0.00602*** (0.000892)	-0.00603*** (0.000894)
Job finding rate (JFR)	0.0101*** (0.00235)	0.00756*** (0.00163)	0.00752*** (0.00157)	0.00577*** (0.00102)	0.00508*** (0.000933)	0.00651*** (0.00148)	0.00628*** (0.00151)
Young × JFR	-0.0106*** (0.00313)	-0.0109*** (0.00327)	-0.0106*** (0.00303)	-0.00898*** (0.00255)	-0.00903*** (0.00257)	-0.00627*** (0.00158)	-0.00629*** (0.00158)
Observations	7730144	7730144	7730143	7730026	7730026	7711419	7711419
R-squared	0.868	0.871	0.872	0.875	0.875	0.895	0.895
Controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Worker FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	No	No	No	No
CZ FE	No	No	No	No	Yes	No	Yes
Firm FE	No	No	No	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	No	No	Yes	Yes
Year x Industry FE	No	No	No	Yes	Yes	No	No

Notes: This table presents the 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 2022, with the dependent variable being the log of yearly real hourly wages. The sample is further limited to the working-age population aged 30 to 52. 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, and is log-transformed. Note that the log-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 commuting-zone level and reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table B4: Young firm and job-finding rate (full sample)

Young	-0.0254*** (0.00168)	-0.0277*** (0.000885)	-0.0245*** (0.000846)	-0.0269*** (0.000711)	-0.0269*** (0.000708)	-0.00461*** (0.000664)	-0.00459*** (0.000669)
Job finding rate (JFR)	0.0129*** (0.00133)	0.00754*** (0.00134)	0.00753*** (0.00133)	0.00584*** (0.000684)	0.00562*** (0.000784)	0.00567*** (0.00125)	0.00570*** (0.00131)
Young $\times$ JFR	-0.00230*** (0.000556)	-0.00959*** (0.00267)	-0.00952*** (0.00238)	-0.00734*** (0.00181)	-0.00739*** (0.00181)	-0.00528*** (0.00135)	-0.00525*** (0.00133)
Observations	14262996	14262996	14262995	14262920	14262920	14243202	14243202
R-squared	0.831	0.857	0.859	0.862	0.862	0.880	0.880
Controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Worker FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	No	No	No	No
CZ FE	No	No	No	No	Yes	No	Yes
Firm FE	No	No	No	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	No	No	Yes	Yes
Year x Industry FE	No	No	No	Yes	Yes	No	No

Notes: This table presents the 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 2022, 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 commuting-zone level and reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table B5: Young firm and job-finding rate (high-tech)

Young	-0.0291*** (0.00241)	-0.0282*** (0.00211)	-0.0286*** (0.00214)	-0.0312*** (0.00291)	-0.0312*** (0.00292)	-0.00951*** (0.00197)	-0.00951*** (0.00197)
Job finding rate (JFR)	0.0111*** (0.00194)	0.00792*** (0.00179)	0.00785*** (0.00174)	0.00576*** (0.00126)	0.00493*** (0.00127)	0.00690*** (0.00157)	0.00666*** (0.00162)
Young $\times$ JFR	-0.0109*** (0.00379)	-0.0110*** (0.00386)	-0.0112*** (0.00346)	-0.0122*** (0.00357)	-0.0123*** (0.00358)	-0.00594*** (0.00205)	-0.00601*** (0.00207)
Observations	2088240	2088240	2088239	2088226	2088226	2085613	2085613
R-squared	0.892	0.896	0.896	0.898	0.898	0.910	0.910
Controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Worker FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	No	No	No	No
CZ FE	No	No	No	No	Yes	No	Yes
Firm FE	No	No	No	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	No	No	Yes	Yes
Year x Industry FE	No	No	No	Yes	Yes	No	No

Notes: This table presents the 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 2022, with the dependent variable being the log of yearly real hourly wages. The sample is further limited to the working-age population aged 30 to 52 employed in high-tech industries. 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 commuting-zone level and reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table B6: Young firm and job-finding rate (establishment)

Young	-0.0319*** (0.00106)	-0.0318*** (0.000959)	-0.0299*** (0.00107)	-0.0315*** (0.00133)	-0.0315*** (0.00132)	-0.0147*** (0.000898)	-0.0147*** (0.000896)
Job finding rate (JFR)	0.0105*** (0.00230)	0.00783*** (0.00157)	0.00778*** (0.00154)	0.00617*** (0.000989)	0.00548*** (0.000915)	0.00665*** (0.00148)	0.00663*** (0.00152)
Young $\times$ JFR	-0.00934*** (0.00254)	-0.0102*** (0.00273)	-0.00962*** (0.00269)	-0.00985*** (0.00256)	-0.00995*** (0.00257)	-0.00568*** (0.000888)	-0.00569*** (0.000880)
Observations	7433120	7433120	7433116	7432978	7432978	7410093	7410093
R-squared	0.867	0.870	0.871	0.874	0.874	0.897	0.897
Controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Worker FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	No	No	No	No
CZ FE	No	No	No	No	Yes	No	Yes
Estab. FE	No	No	No	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	No	No	Yes	Yes
Year x Industry FE	No	No	No	Yes	Yes	No	No

Notes: This table presents the 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 2022, with the dependent variable being the log of yearly real hourly wages. The sample is further limited to the working-age population aged 30 to 52. Instead of defining the employer as the firm, we define it as the workplace, or establishment. Young establishments 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 commuting-zone level and reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table B7: Summary statistics: Demographic information

Panel A. Survey sample

	Mean	SD	P10	Median	P90	N
Age	52.28	10.91	36.00	55.00	64.00	2556
Male (= 1)	0.60	0.49	0.00	1.00	1.00	2556
Number of kids	0.69	0.97	0.00	0.00	2.00	2556
College (= 1)	0.46	0.50	0.00	0.00	1.00	2556
Income (DKK)	430558.95	316162.37	253611.00	384364.20	616703.09	2556
Mortgage (= 1)	0.68	0.47	0.00	1.00	1.00	2556
Leverage	0.31	0.64	0.00	0.21	0.58	2556

Panel B. Full sample with employed workers

	Mean	SD	P10	Median	P90	N
Age	42.10	15.01	22.00	42.00	62.00	2975127
Male (= 1)	0.52	0.50	0.00	1.00	1.00	2975127
Number of kids	0.89	1.07	0.00	0.00	2.00	2975127
College (= 1)	0.37	0.48	0.00	0.00	1.00	2975127
Income (DKK)	331183.89	780811.21	96230.00	303133.00	523254.97	2975127
Mortgage (= 1)	0.48	0.50	0.00	0.00	1.00	2975046
Leverage	0.39	0.79	0.00	0.20	0.78	2973577

Notes: This table presents summary statistics on worker demographics for the survey sample and the full labor force. ‘Male (= 1)’, ‘College (= 1)’, and ‘Mortgage (= 1)’ are indicator variables equal to one if a worker is male, holds a college degree, and has a mortgage, respectively.