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The Ronald O. Perelman Center for Political Science and Economics (PCPSE)
133 South 36th Street
Philadelphia, PA 19104-6297

pier@econ.upenn.edu
http://economics.sas.upenn.edu/pier

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Defensive Hiring and Creative Destruction

JESÚS FERNÁNDEZ-VILLAVERDE
University of Pennsylvania

YANG YU
Shanghai Jiao Tong University

FRANCESCO ZANETTI
University of Oxford

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Jesús Fernández-Villaverde[†] Yang Yu[‡] Francesco Zanetti[♭]

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Abstract

Defensive hiring of researchers by incumbent firms with monopsony power reduces creative destruction. This mechanism helps explain the simultaneous rise in R&D spending and decline in TFP growth in the US economy over recent decades. We develop a simple model highlighting the critical role of the inelastic supply of research labor in enabling this effect. Empirical evidence confirms that the research labor supply in the US is indeed inelastic and supports other model predictions: incumbent R&D spending is negatively correlated with creative destruction and sectoral TFP growth while extending incumbents' lifespan. All these effects are amplified when ideas are harder to find. An extended version of the model quantifies these mechanisms' implications for productivity, innovation, and policy.

Keywords: Productivity growth, innovation, R&D, patents, creative destruction.

JEL Classification: E22, L11, O31, O33.

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[†]Jesús Fernández-Villaverde: University of Pennsylvania, US jesusfv@econ.upenn.edu; [‡]Yang Yu: Shanghai Jiao Tong University, China. yu.yang.econ@sjtu.edu.cn; [♭]Francesco Zanetti: University of Oxford, U.K. francesco.zanetti@economics.ox.ac.uk.

1 Introduction

Creative destruction and productivity growth have sharply declined in the US over the past two decades, despite a substantial rise in R&D spending and the hiring of specialized workers (*researchers*).[1] Why has higher R&D spending failed to translate into stronger innovation and productivity gains? What mechanisms drive this divergence? And what are their implications for innovation, productivity growth, and economic policy?

We argue that *defensive hiring* –where incumbents recruit researchers to raise wage costs for potential entrants– drives this dynamic, though not exclusively. This strategy is most effective when the researcher labor supply is inelastic and when the incumbent has more value to protect. Given equal firm value, smaller incumbents raise wages more. We show that defensive hiring helps explain lower TFP growth alongside higher researcher numbers, specialization, and compensation in the US from 1929 to 2020.

After presenting motivating, unified evidence on TFP, R&D spending, firm entry, and the number and compensation of researchers in the US, we start by developing a simple theoretical model of creative destruction in monopsony markets for researchers based on the Aghion-Howitt model of Shumpeterian destruction (Aghion and Howitt, 1992). We show that two key forces operate within this framework. On one hand, incumbent firms want to exploit their monopsony power by underpaying researchers relative to a competitive market. On the other hand, they engage in a defensive hiring strategy by employing a large number of researchers at above-competitive-market wages to reduce the probability that competitors will innovate, thus decreasing creative destruction.

We characterize the conditions under which defensive hiring outweighs the monopsony-power mechanism. Specifically, we show that defensive hiring becomes the dominant force when: (i) the size of innovation is small; (ii) the entrants have low R&D efficiency; and (iii) the entry cost is high. Since the first two conditions lead to a reduction in the size and likelihood of innovation, defensive hiring prevails when "ideas are getting harder to find" (Bloom et al., 2020).

Given that the strength of defensive hiring depends crucially on the elasticity of the labor

[1] We define *researchers* broadly to include any worker engaged in innovation within a firm, even if not directly involved in classic R&D. This includes, for example, a systems analyst optimizing logistics or a software engineer improving operational efficiency.

supply of researchers, we provide new estimates of level, trend, and variations of the labor supply among industries. We do so by assembling a novel dataset that combines the innovations of individual inventors elicited from the universe of patent applications recorded by the US Patent and Trademark Office for the period 1970-2019 with the returns of those innovations to the inventors from stock market price data. By linking individual inventors –a proxy for researchers in the model– to the market value of their patents elicited from stock market prices –the empirical counterpart of the payoff for conducting research– we establish three new facts:

Fact 1. The labor supply of researchers is inelastic. A 1% increase in the average market value of patents in a research field (adjusted for the number of coinventors), which is our proxy for the expected payoff to inventors for undertaking research effort, attracts an additional 0.14% of inventors applying for patents in the same field.

Fact 2. The elasticity of the labor supply of researchers has decreased over time, from a value of 0.17 between 1970 and 1995 to 0.07 between 1996 and 2019 (the full sample point estimate is 0.14, as established in Fact 1). In other words, the labor supply of researchers has become increasingly inelastic over time.

Fact 3. Since industries are exposed to research fields in different ways, the elasticity of the labor supply of researchers is strongly heterogeneous across industries.

Furthermore, our simple theoretical model yields four sharp, testable implications of the impact of R&D by incumbents: (i) it negatively affects new firm entry; (ii) it positively affects the lifespan of incumbent firms; (iii) it hinders technological growth when the incumbent firms' R&D efficiencies are sufficiently low; and (iv) these effects are stronger when the supply of researchers is inelastic.

We test these theoretical predictions by merging our data on patents and stock market returns on inventions with R&D spending data from Compustat Fundamental Annual data, sectoral TFP from the Bureau of Labor Statistics covering 90 four-digit NAICS industries, and firm entry from the Business Dynamics Statistics covering 281 four-digit NAICS industries. By doing so, we establish three additional new facts that corroborate our theoretical preditions:

Fact 4. Incumbents' R&D spending negatively predicts the creation of new firms in the same industry. The prediction is stronger in industries with a lower elasticity of research labor supply.

Fact 5. Incumbents' R&D spending positively predicts the lifespan of the incumbent firms.

The prediction is stronger in industries with a lower elasticity of research labor supply.

Fact 6. Incumbents' R&D spending negatively predicts TFP growth for firms in the same industry. The prediction is stronger in industries where research labor supply is less elastic.

Having empirically validated our model, we extend it into a quantitative framework to assess the implications of defense hiring in general equilibrium and conduct counterfactual policy analysis. In the model, workers choose between research and production occupations. The share of researchers in total employment depends on the wage gap between these occupations and workers' preference distribution. Researchers are randomly assigned to sectors but can switch at a cost, which endogenously determines the equilibrium elasticity of the research labor supply. We calibrate the model to US data.

Our quantitative analysis yields six results. First, defensive hiring prevails over monopsony power when determining researchers' wages in our calibrated model. Incumbent firms strategically set higher wages and recruit researchers aggressively, leading to low creative destruction and business dynamism. This hurts technological growth due to the lower R&D efficiency of incumbents compared to entrants.

Second, the higher wages set by incumbent firms encourage more workers to choose research careers. This is a general equilibrium effect that enhances technological growth, similar to a subsidy for choosing a research occupation. However, this benefit is dominated by the preceding detrimental effect of defensive hiring on creative destruction.

Third, an increase in the switching cost for researchers, consistent with the deepening specialization of research (Yang and Borland, 1991), leads to a decline in the elasticity of the research labor supply, a fall in creative destruction, a rise in the population of researchers, a higher wage premium for researchers, and a drop in technological growth, broadly consistent with the empirical patterns in the past few decades. The government can partially reverse the above trends by reducing switching costs. Policies such as advocating affordable online courses and promoting interdisciplinary research are likely effective.

Fourth, the motive for defensive hiring is stronger when the R&D efficiency of entrants is lower. In other words, the incumbent firms would suppress creative destruction more aggressively when ideas are getting harder to find (Bloom et al., 2020).

Fifth, the government can subsidize new entrants and tax incumbents to promote technological growth and correct market distortions. Taxing incumbents strengthens the monopsony effect, curbing defensive hiring. This approach contrasts with traditional models, which propose subsidizing incumbents to counteract monopsony effects.

Finally, we distinguish between short- and long-run research labor supply elasticities, which are only mildly correlated across fields and industries. Facts 4-6 hold only for short-run elasticities, suggesting that incumbents' strategic behavior is driven by short- rather than long-run factors. To reconcile both observations, we extend our model to allow researchers to shift fields over time, reducing distortions and moderating excessive wages. Specifically, we identify a new mechanism: the *dynamic attraction effect*, where higher wages today draw more researchers in the future, reducing incumbents' future value.

Our analysis is related to research on how incumbents' strategic R&D behavior affects technological growth. Argente et al. (2020) and Akcigit and Goldschlag (2023) show that large firms' R&D spending deters competition without sustaining innovation. Bloom et al. (2020) and Bilal et al. (2021) find that slower idea generation hinders creative destruction. Cunningham et al. (2021), Bao and Eeckhout (2023), and Benkert et al. (2023) show that incumbents use R&D and acquisitions to consolidate market power. We demonstrate that the defensive hiring of researchers is an effective strategy in monopsony markets with low labor supply elasticity.

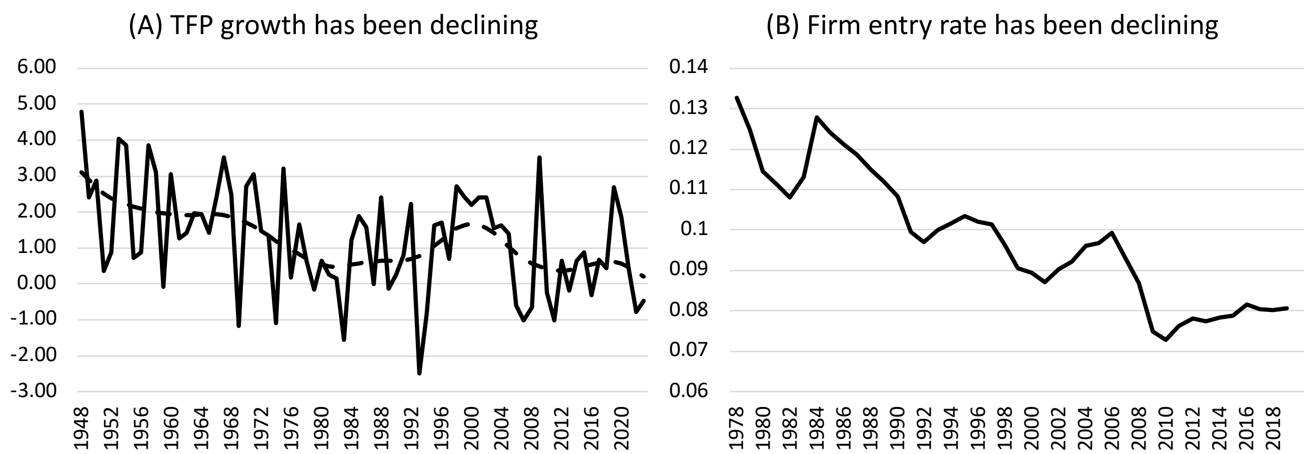
We also contribute to the literature on monopsony power. Most research (Azar et al., 2019; Berger et al., 2022; Manning, 2021) examines classic monopsony markets, where dominant firms set below-competitive wages while under-hiring workers. Our paper is closer to Parente and Prescott (1999) and Fernández-Villaverde et al. (2021), who show that dominant firms expand hiring to reinforce monopsony power in product and labor markets, contrary to classic monopsony predictions. Unlike prior work focused on declining labor share and rising market concentration, our paper explores how monopsony power in researchers' labor market affects technological growth.

The paper is structured as follows. Section 2 presents motivating evidence. Section 3 develops a model of creative destruction in monopsonistic research labor markets. The empirical results are presented in Sections 4 and 5. Section 6 extends the model for quantitative analysis and policy implications. Section 7 presents the main quantitative results. Section 8 concludes. An online Appendix provides further details.

2 Motivating evidence

This section presents a unified analysis of TFP, R&D spending, firm entry, and the number and compensation of US researchers from 1929 to 2020. Using annual data from multiple sources, we document a persistent decline in TFP growth and creative destruction despite steady increases in the number and remuneration of researchers.

Figure 1: TFP growth and the rate of entry of new firms in the US economy



Panel (A) of Figure 1 presents annual utilization-adjusted TFP growth (solid line), constructed following Fernald (2014), alongside its HP-filtered trend (dashed line) from 1948 to 2023. The figure illustrates a gradual decline in TFP growth, consistent with findings from Gordon (2012), Akcigit and Ates (2021), and Acemoglu et al. (2023).

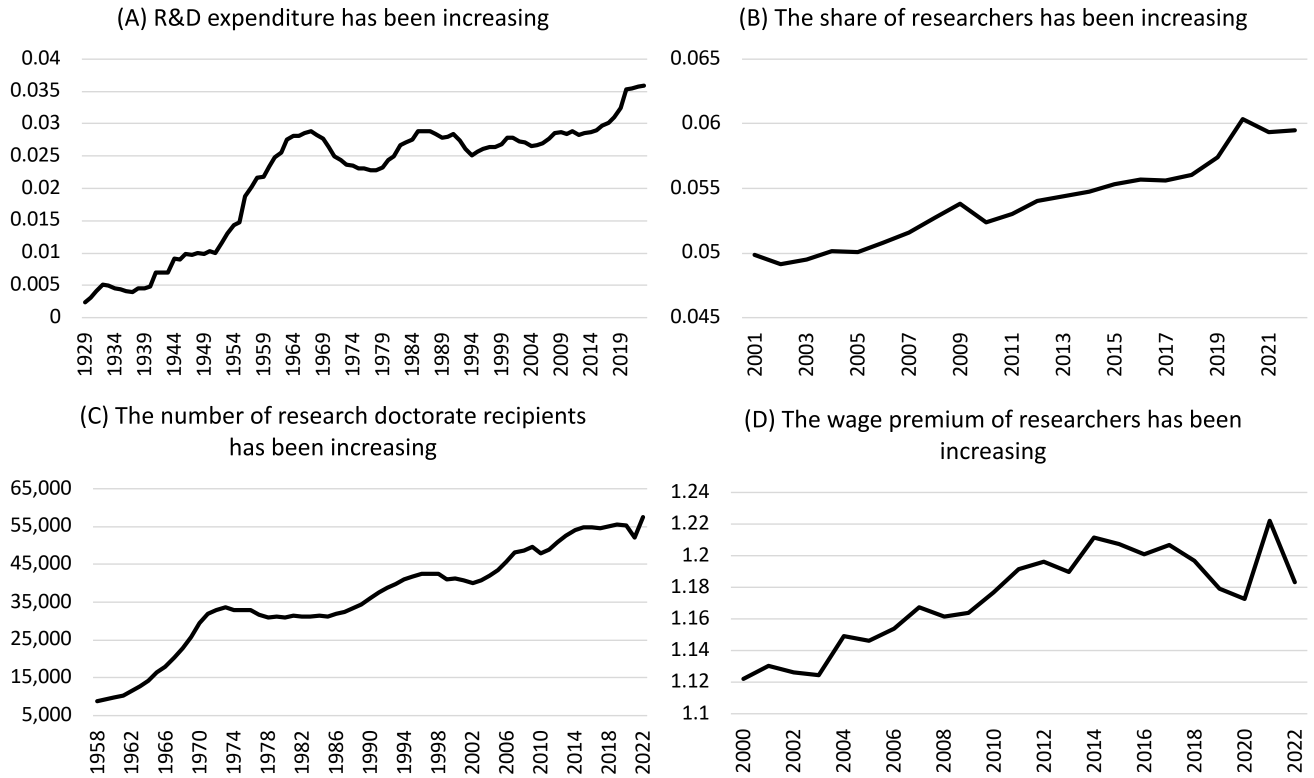
Panel (B) displays the annual firm entry rate from 1978 to 2018, measured as the ratio of new firms to total firms in the Business Dynamics Statistics (BDS) dataset administered by the US Census Bureau. The figure shows a steady decline in firm entry, aligning with findings from Decker et al. (2020) and Akcigit and Ates (2023).

Panel (A) of Figure 2 presents R&D expenditure as a share of GDP from 1929 to 2020, using data from the Bureau of Economic Analysis (BEA). The figure shows a mostly uninterrupted rise in R&D spending over the past century.

Panel (B) of Figure 2 presents the share of researchers in total employment from 2001 to 2022, showing an upward trend consistent with rising R&D spending.[2]

[2]Research occupations include Computer and Mathematical Occupations (occupation code 15-0000) and Life,

Figure 2: R&D expenditure, number and wage of researchers in the US



Panel (C) displays the annual number of research doctorate recipients from 1958 to 2022 based on National Science Foundation (NSF) data. The series exhibits a twelvefold increase since 1958, reflecting a sharp rise in the inflow of doctorate researchers, which partially explains the employment growth in Panel (B).

Panel (D) presents the ratio of median annual wages for research occupations to those of workers with at least an undergraduate degree, based on Bureau of Labor Statistics (BLS) data from 2000 to 2022. The figure shows that research occupations have seen faster wage growth than the broader college-educated workforce.

We quantify wage differences between research and non-research occupations and their trends by estimating:

$$\ln(W_{i,t}) = a \cdot RO_{i,t} + b \cdot RO_{i,t} \times t + c \cdot X_{i,t} + \epsilon_{i,t},$$

where the dependent variable is the logarithm of worker i's annual wage in year t. The key independent variable, $RO_{i,t}$, is a dummy equal to one if the worker is in a research occupation.

Physical, and Social Science (occupation code 19-0000). Data are from the BLS.

The interaction term, $RO_{i,t} \times t$, captures the trend in the research wage premium, with a positive b indicating a widening gap. The control vector $X_{i,t}$ includes the logarithm of age, gender, industry fixed effects, and education-by-year fixed effects.[3]

With these controls, our estimation captures cross-sectional differences between occupations, conditional on identical educational attainment and demographic characteristics. Our sample spans 2001-2019, focusing on workers with a college degree or higher. The data come from the American Community Survey, accessed via IPUMS.[4]

Table 1: Research wage premium has been increasing

	(1)	(2)
Research occupation	0.141***	-7.782***
	(0.001)	(0.379)
Research occupation×Year		0.004***
		(0.0002)
Controls	Yes	Yes
Industry FE	Yes	Yes
Education-by-Year FE	Yes	Yes
Observations	7,480,172	7,480,172

The data span 2001-2019 on a yearly basis, restricted to workers with a college degree or higher. The dependent variable is the log wage, while the key independent variable is a research occupation dummy, equal to one if the worker's occupation is research-related. Control variables include log age and gender.

Table 1 presents the estimation results. Column (1) shows that research occupations earn an average wage premium of 14.1% over other occupations. Column (2) indicates that this premium grows at an annual rate of 0.4%, an economically significant increase.

In summary, TFP growth rates and new firm entry have declined significantly, despite substantial increases in aggregate R&D spending, researcher numbers, and remuneration. Next, we develop a theory that reconciles these seemingly contrasting empirical patterns.

3 A simple model of creative destruction and monopsony

Building on Aghion and Howitt (2005), we develop a simple model of creative destruction in a monopsonistic researcher market. The core mechanism stems from the interplay between

[3]The education-by-year fixed effects account for both differences across education groups and time-varying education premiums.

[4]Data are available only in decennial intervals before 2000. Including these earlier data would likely show an even steeper growth in the research wage premium, as research-related occupations generally had lower wages relative to non-research occupations during that period.

defensive hiring and inelastic researcher supply. Our framework explains the patterns in Section 2 and yields testable predictions on creative destruction and technological growth, analyzed in Sections 4 and 5. Section 6 extends the model to explore its quantitative and policy implications.

3.1 Incumbents and entrants

The economy consists of J sectors, each with an incumbent firm holding monopoly power and producing one unit of non-storable goods at a unitary marginal cost. The incumbent sets the price at $\chi > 1$, earning an operating profit (i.e., profit before R&D expenses) $\pi = \chi - 1$. Since sectors are symmetric, we omit the sectoral index.

The incumbent faces competition from an infinite number of entrants. Both incumbents and entrants hire researchers to innovate and produce the same good at a unitary marginal cost but with improved quality. Higher quality increases the value of output by $\gamma > 1$.

If the incumbent innovates, it retains its position and earns a new operating profit $\gamma\pi$. If neither the incumbent nor an entrant innovates, the incumbent remains but earns only π. The incumbent's innovation probability is $f_I = \phi n_I$, where n_I is the number of researchers hired, and $\phi > 0$ represents R&D efficiency.

If an entrant innovates, creative destruction occurs: the entrant displaces the incumbent, becomes the new market leader, and sells at price $\chi > 1$ with operating profit $\gamma\pi - \iota$, where ι is a fixed entry cost. The incumbent and unsuccessful entrants then earn zero profits and exit.[5]

Each sector has a continuum of potential entrants with stochastic R&D efficiency $k > 0$, distributed by the c.d.f. $\Psi(k)$. The total measure of potential entrants is $\psi = \Psi(+\infty)$. Without loss of generality, we assume each entrant hires one researcher at the sectoral wage w.

Since free entry drives profits to zero in equilibrium, entrants must have a sufficiently high probability of innovating ($\underline{k}$) to remain in the market. We determine $\underline{k}$ below when deriving the model equilibrium. Thus, the employment of researchers by entrants is:

$$n_E = \int_{\underline{k}}^{+\infty} 1 d\Psi(k) = \psi - \Psi(\underline{k}), \tag{1}$$

and the innovation probability for entrants is:

$$f_E = \int_{\underline{k}}^{+\infty} k d\Psi(k). \tag{2}$$

[5] We assume ϕ and n_I keep f_I within (0,1). Also, each period is short enough that only either the incumbent or the entrant can innovate per period. This common assumption simplifies algebra without affecting results.

The expected growth rate of output in each sector, $g = \gamma(f_I + f_E)$, equals the value of the innovated output times the probability of innovation from either the incumbent or the entrant.

3.2 The supply of researchers

The aggregate supply of researchers is fixed at $\overline{N}$, and the labor supply, $N(w)$, in each sector is proportional to the sectoral-to-aggregate wage ratio:

$$N(w) = \frac{\overline{N}}{J}\left(\frac{w}{W}\right)^{\eta}, \tag{3}$$

where W is the aggregate wage index taken as given by firms.

The parameter $\eta > 0$ controls the elasticity of sectoral labor supply for researchers, generating the standard positively sloped supply curve, i.e., $N'(w) > 0$. For now, $\overline{N}$ and η are exogenously given. However, in the quantitative version of the model, they will be endogenously determined. The labor market clears in each sector, i.e., $N(w) = n_I + n_E$.

3.3 The Stackelberg two-stage hiring game

The incumbent strategically hires researchers, as the established wage affects both researcher supply and entrants' innovation probability, threatening its survival. Hiring follows a Stackelberg two-stage game. In the first stage, the incumbent sets w, determining the sector's researcher supply, and hires accordingly. In the second stage, entrants hire from the remaining researcher pool, taking w as given. We solve for equilibrium by backward induction.

Stage 2: Entry decision of the entrants. A potential new firm enters the economy if its expected profit, $k(\gamma\pi - \iota) - w$, is positive. By free entry, there is an R&D efficiency threshold, $\underline{k}(w)$ that ensures zero expected profits:

$$\underline{k}(w) = w/(\gamma\pi - \iota). \tag{4}$$

Firms above this threshold will enter and innovate; firms below it will not.

By combining equations (2)-(4), we find that a higher equilibrium wage reduces the measure of entry and suppresses the process of creative destruction by lowering the profitability of new entrants:

$$n_E^{'}(w) = -\frac{\Psi^{'}(\underline{k})}{\gamma\pi - \iota} < 0 \text{ and } f_E^{'}(w) = -\frac{\underline{k}\Psi^{'}(\underline{k})}{\gamma\pi - \iota} < 0. \tag{5}$$

No entrant has an incentive to deviate from the wage w set by the incumbent. First, in equilibrium, all researchers are employed at w, so they will not accept a lower wage. Second, since entrants can hire researchers at w, raising wages above it would only reduce their profits. Thus, each entrant sets its wage at w to maximize profits.[6]

Stage 1: Wage setting of the incumbent. The incumbent firm selects the number of researchers and sets the wage to maximize its profits:

$$\max_{w,n_I} \phi n_I \gamma \pi + [1 - \phi n_I - f_E(w)]\, \pi - n_I w, \tag{6}$$

subject to the market-clearing condition in the sectoral labor market:

$$n_I(w) = N(w) - n_E(w). \tag{7}$$

In equation (6), ϕn_I is the probability that the incumbent firm successfully innovates, yielding the profit $\gamma\pi$. The second term captures the profits when neither the incumbent nor the entrants successfully innovate, which occurs with probability $1 - \phi n_I - f_E(w)$, resulting in the continuation of the initial profit π. The third term accounts for the wage cost of research labor.[7] From now on, we will write equation (6) as $(\gamma - 1)\phi\pi n_I(w) + [1 - f_E(w)]\pi - n_I(w)w$.

Since we already saw that $N'(w) > 0$ and $n_E'(w) < 0$, we get:

$$n_I'(w) = N'(w) - n_E'(w) > 0, \tag{8}$$

i.e., the hiring of the incumbent firm is positively related to w. In other words, the incumbent firm must hire more workers to increase w, or, conversely, it must increase w to hire more workers.

Combining equations (4) and (8), we derive the impact of hiring researchers by the incumbent firm on the probability of creative destruction:

$$\frac{df_E}{dn_I} = \frac{df_E/dw}{dn_I/dw} = \frac{f_E'(w)}{N'(w) - n_E'(w)} < 0. \tag{9}$$

Equation (9) yields three results. First, increased incumbent hiring lowers creative destruction. Second, this effect is stronger when the sectoral research labor supply is inelastic, i.e., $N'(w)$ is low. Third, the deterrent effect intensifies when entrants' innovation is highly wage-sensitive, i.e., the absolute value of $f_E'(w)$ is high. Using equation (5), this occurs when the expected profits from innovation $(\gamma\pi - \iota)$ are low or when potential entrants are concentrated near the entry

[6] For potential entrants that do not enter at wage w (i.e., $k(\gamma\pi - \iota) - w < 0$), offering a higher wage $w' > w$ does not incentivize entry, as $k(\gamma\pi - \iota) - w' < k(\gamma\pi - \iota) - w < 0$.

[7] Equation (6) also includes the implicit term $f_E(w) \cdot 0$, reflecting that the incumbent firm exits the market and earns zero profit with the probability of creative destruction, $f_E(w)$.

threshold ($\Psi'(\underline{k})$).

3.4 Optimal conditions for the incumbent firm

Before solving the two-stage hiring game and deriving the model equilibrium, we first analyze optimality in competitive and classic monopsony markets, which serve as benchmarks for the game's solution.

Competitive market. In this case, the incumbent firm takes w as given and chooses n_I by maximizing profits:

$$\max_{n_I} (\gamma - 1)\phi\pi n_I + (1 - f_E)\pi - n_I w, \tag{10}$$

yielding the standard optimality condition that equates w to the marginal product of researchers (mpr):

$$\overbrace{w}^{\text{wage}} = \overbrace{(\gamma - 1)\,\phi\pi}^{\text{mpr}}.$$

Classic monopsony market. In this case, the incumbent firm internalizes the effect of w on labor supply but still takes the probability of creative destruction, f_E, and the hiring by the entrants, n_E, as given:

$$\max_{w} (\gamma - 1)\phi\pi n_I(w) + (1 - f_E)\pi - n_I(w)w,$$

where $n_I(w) = N(w) - n_E$.

The optimality condition is:

$$\overbrace{w}^{\text{wage}} = \overbrace{(\gamma - 1)\,\phi\pi}^{\text{mpr}} - \overbrace{\frac{n_I(w)}{N'(w)}}^{\text{monopsony}}, \tag{11}$$

which mirrors the competitive case but includes an additional term that lowers the wage and captures the monopsony power. This distortion is stronger when the labor supply is inelastic, i.e., when $N'(w)$ is low.[8] In this case, a decrease in the elasticity of the sectoral research labor supply lowers wages and reduces researcher hiring, contradicting observed trends.

The two-stage game. Now the incumbent firm internalizes the effect of w on the entrants' innovation probability, f_E, through its effect on the number of researchers, n_E. Thus, the

[8]This condition is just the classic wage markdown formula, $\left[1 + \frac{1}{\eta} \cdot \frac{n_I(w)}{N(w)}\right] w = (\gamma - 1)\phi\pi$.

incumbent's problem is still

$$\max_{w}(\gamma-1)\phi\pi n_I(w)+[1-f_E(w)]\pi-n_I(w)w,$$

where $n_I(w)=N(w)-n_E(w)$, but now we differentiate with respect to w in $f_E(w)$ and $n_E(w)$.

The resulting optimality condition is:

$$\overbrace{w}^{\text{wage}}=\overbrace{(\gamma-1)\,\phi\pi}^{\text{mpr}}-\frac{\overbrace{n_I(w)}^{\text{monopsony}}+\overbrace{f_E'(w)\pi}^{\text{defensive hiring}}}{n_I'(w)} \tag{12}$$

Compared to the classic monopsony result in equation (11), we now have an additional term, $f_E'\pi$, which reflects the incumbent's incentive to raise wages to deter entry (recall that $f_E'<0$ and $n_I'(w)>0$). This reduces the probability of creative destruction, f_E, by increasing the R&D efficiency threshold for potential entrants to achieve zero expected profit. We refer to this mechanism as defensive hiring.

The relative strength of the two opposing forces determines whether the incumbent firm would set a higher or lower wage than in the competitive case.

Case 1: $n_I>|f_E'\pi|$**.** When incumbent employment is high relative to $|f_E'\pi|$, wage costs become critical. The classic monopsony incentive dominates, leading the firm to under-hire and set a lower wage than in the competitive case, increasing firm entry. This effect is amplified when the labor supply elasticity of researchers, $N'(w)$, is low, as it reduces the denominator of equation (12). Conversely, when the labor supply of researchers becomes infinitely elastic ($N'(w)\to+\infty$), the distortion disappears, and the model converges to the competitive case.

Case 2: $n_I<|f_E'\pi|$**.** When incumbent employment is low relative to $|f_E'\pi|$, wage costs matter less, leading the incumbent to over-hire and set a higher wage than in a competitive market, restricting entry. As before, this effect is stronger when $N'(w)$ is low. Notably, our analysis suggests that, given on the same level of π, smaller incumbents are more likely to engage in defensive hiring than larger ones.

To understand better when $n_I<|f_E'\pi|$, we combine equations (4) and (5), yielding:

$$f_E'\pi=-\frac{\pi w\Psi'(\underline{k})}{(\gamma\pi-\iota)^2}. \tag{13}$$

Equation (13) shows that the incumbent over-hires researchers relative to the competitive economy when: (i) innovation size, γ, is small; (ii) the fixed cost for new entrants, ι, is high; and (iii) the density of potential entrants near the entry threshold, $\Psi'(\underline{k})$, is high. Additionally, defensive hiring intensifies when the labor supply is inelastic.

Condition (iii) aligns with the empirical evidence that ideas are becoming harder to find (Bloom et al., 2020). Potential entrants near the entry threshold typically have lower R&D efficiency, leading to a more left-skewed distribution and greater difficulty in discovering ideas. This allows incumbents to deter new entrants more effectively. Additionally, condition (i) holds when good ideas are becoming scarcer.

The relationship between defensive hiring and technological growth. While defensive hiring stifles creative destruction, its overall effect on technological growth is ambiguous, as it increases the incumbent's innovation rate, f_I,. The net impact on technological growth depends on the R&D efficiency of the incumbent relative to that of marginal entrants.

Suppose incumbents in all sectors raise wages by Δw, leading to an increase in the technological growth rate:

$$\Delta g = \gamma(\Delta f_I + \Delta f_E) = \frac{(\phi - \underline{k})\Psi'}{\gamma\pi - \iota}\Delta w, \tag{14}$$

showing that defensive hiring reduces technological growth if and only if $\phi < \underline{k}$. While ϕ is exogenous, $\underline{k}$ is determined endogenously by the free-entry condition (4): $w/(\gamma\pi - \iota)$. A high $\underline{k}$ (i.e., a greater likelihood that defensive hiring harms technological growth) results from a low innovation size γ, low innovation profit π, or high fixed cost ι.

Defensive hiring hinders technological growth when: (i) the incumbent's R&D efficiency is low; (ii) innovation size is small; (iii) innovation profit is low; and (iv) the fixed cost for successful entrants is high. While our model abstracts from occupational choices between R&D and non-R&D roles, it is likely that, in practice, defensive hiring raises R&D wages, attracting more workers to the field. We defer the discussion of this general equilibrium effect to Section 6.

4 The elasticity of researcher labor supply

Our theory identifies the elasticity of researcher labor supply as a key factor linking defensive hiring and creative destruction. In this section, we show that this elasticity is low on average, has declined over time, and varies across research fields and industries. These facts suggest that defensive hiring is a significant?and increasingly important?mechanism in the data.

Data on inventors and patents' value. Obtaining a comprehensive account of all workers involved in R&D within an economy is challenging. For instance, is a human resources specialist hiring scientists for a research lab part of R&D? Not directly, yet the specialist is essential for the lab's functioning. Given these complexities, we follow a common approach in the literature and focus on inventors –a subset of "core" researchers– as a proxy measurement of all researchers.

We obtain inventor data from patent application records compiled by the US Patent and Trademark Office (USPTO). The dataset spans 1970 to 2019, covering over seven million inventors and eleven million patent applications. These applications are categorized into 132 Cooperative Patent Classification (CPC) classes (e.g., Organic Chemistry), which we refer to as research fields.[9] Approximately 64% of applications are successfully granted.

Our first objective is to measure how inventors allocate their research labor across fields. Let $m_t(\zeta)$ be the number of patent applications filed by inventor ζ in year t. Assuming inventors distribute effort equally across patents and normalizing annual research effort to one, ζ spends $1/m_t(\zeta)$ units of labor per patent.

We define $\omega_{k,t}(\zeta)$ as the subset of inventor ζ's patent applications in field k. For patents classified in multiple fields, we assign a weight of $1/n_i$, where n_i is the number of fields patent i belongs to. Thus, by working on patent $i \in \omega_{k,t}(\zeta)$, inventor ζ contributes $1/[m_t(\zeta)n_i]$ units of labor to field k. Inventor ζ's research labor supply to field k is then:

$$l_{k,t}(\zeta) = \sum_{i \in \omega_{k,t}(\zeta)} \frac{1}{m_t(\zeta)n_i},$$

and the total research labor supply to field k is the sum of $l_{k,t}(\zeta)$ across inventors $L_{k,t} = \sum_{\zeta} l_{k,t}(\zeta)$.

Our second goal is to examine what determines an inventor's allocation of research labor to a specific field. A natural candidate is the expected monetary payoff from research.[10] We assume that an inventor's monetary payoff is proportional to the patent's market value, adjusted for the number of coinventors and their labor contributions. This assumption is justified by the role that stocks and options play in researchers' compensation in many industries. Additionally, bonuses, wage raises, and promotions are often linked with a researcher's contribution to firm

[9] We exclude applications filed after 2019, as many remain ungranted due to the lengthy examination process. We also exclude applications with unidentified CPC classes. Our results remain robust when defining research fields using the United States Patent Classification, which offers broader coverage for patents filed before 2001 but was largely phased out after 2013.

[10] Other factors include intrinsic motivation, curiosity, reputation, and social responsibility, which are difficult to measure and beyond this paper's scope.

value. Moreover, in models where a worker (an inventor) and a firm negotiate compensation via Nash bargaining, the worker's gain from effort (developing a patent) is proportional to the firm's incremental value (the patent's market value).[11]

Under this assumption, the payoff per unit of research effort on patent i is:

$$w_i = \frac{v_i}{\sum_{\zeta \in \Phi_i} 1/m_t(\zeta)}, \tag{15}$$

where v_i is the real market value of patent i, as constructed by Kogan et al. (2017), based on stock price reactions to USPTO patent announcements and Φ_i denotes the set of coinventors of patent i. As discussed, $1/m_t(\zeta)$ represents each coinventor ζ's effort on patent i, making $\sum_{\zeta \in \Phi_i} 1/m_t(\zeta)$ the total effort across all coinventors.

Akcigit and Goldschlag (2023) propose an alternative measure of inventors' monetary payoff using tax data. While wages provide an accurate measure of the contemporaneous "wage component," they do not capture changes in expected future income linked to research efforts, such as promised wage increases, promotions, or non-wage compensation (e.g., stocks and options). These elements are crucial to inventors' total monetary payoff and are likely to comove with, and thus be reflected in, a patent's market value. Hence, we consider our measure complementary to that of Akcigit and Goldschlag (2023).

Finally, we compute the average payoff to research effort in field k as:

$$W_{k,t} = p_{k,t} \frac{\sum_{i \in \Omega_{k,t}} w_i / n_i}{\sum_{i \in \Omega_{k,t}} 1/n_i}, \tag{16}$$

where $p_{k,t}$ is the fraction of successfully patented applications, adjusting for the difficulty of obtaining a patent. $\Omega_{k,t}$ denotes the set of patents in field k, and n_i is the number of fields patent i belongs to. We weight patents by $1/n_i$, assigning greater importance to more specialized patents (i.e., those with lower n_i) within a given research field.

Fact 1: The research labor supply is inelastic on average

First, we examine the relationship between expected research income and the labor supply at the extensive margin of researchers. Specifically, we analyze how a transitory increase in the market value of patents in a given field affects the research labor supply in that field.

[11] Appendix B uses simulations to show a strong positive correlation between researcher compensation and the market value of innovation (the theoretical counterpart of the patent), supporting our use of patent market value as a proxy for monetary payoffs in our regressions.

We estimate the elasticity of labor supply, η, our key parameter of interest, by running:

$$\Delta \ln \left(L_{k,t}\right) = \alpha + \eta \Delta \ln \left(W_{k,t}\right) + \chi_t + \gamma_k + \epsilon_{k,t}, \tag{17}$$

where $L_{k,t}$ denotes total research labor supply in field k in year t, and $W_{k,t}$ represents the monetary payoff to research. The subscript t corresponds to the year patent applications are filed, typically after research projects conclude. We assume researchers form expectations about future payoffs that are, on average, accurate –a standard rational expectations assumption. Specifically, when choosing labor supply in year $t - m$ (where m is the research project's duration), they anticipate future payoffs, $\{E_{t-m}\left(W_{k,t}\right)\}_k$, which equal realized payoffs, $\{W_{k,t}\}_k$, plus an unforecastable error term.

The regression includes year fixed effects, χ_t, and research field fixed effects, γ_k, to control for persistent differences in research labor supply across fields. Since labor supply and expected payoffs generally trend upward at varying rates across fields, simple time fixed effects cannot fully account for these differences. Thus, we take the first difference of the log of both variables to ensure stationarity.

A concern with equation (17) is that both $L_{k,t}$ and $W_{k,t}$ may be jointly affected by shifts in labor supply, biasing η downward. For instance, increased graduate fellowships or H1B visas in STEM fields expand the supply of researchers while also prompting firms to initiate more projects and hire more researchers per project. These effects boost innovation probabilities but reduce the individual payoffs in equation (16). Expanding research projects may also lower the patent success rate, $p_{k,t}$, as similar ideas compete for a fixed number of granted patents. Moreover, hiring more researchers per project reduces per-inventor payoffs, w_i, by increasing the denominator in equation (15).

To address endogeneity, we instrument $W_{k,t}$ using two instrumental variables. The first is the average patent value in each research field, unadjusted for the number of inventors and the success rate, $\widehat{W}_{k,t} = \frac{\sum_{i \in \Omega_{k,t}} v_i / n_i}{\sum_{i \in \Omega_{k,t}} 1/n_i}$. By construction, $\widehat{W}_{k,t}$ is positively correlated with $W_{k,t}$ and remains unaffected by researchers' labor supply influencing the patent success rate or the effective number of coinventors.

The second instrument is the average lagged size of innovating firms (i.e., firms employing the inventors), measured by their average real output, $\widehat{Y}_{k,t} = \frac{\sum_{i \in \Omega_{k,t}} Y_{i,t-1} / n_i}{\sum_{i \in \Omega_{k,t}} 1/n_i}$, where $Y_{i,t-1}$ is the lagged annual real output of patent i's innovating firm. The rationale for this instrument is that larger firms commercialize patents on a larger scale, increasing their value. Crucially, the lagged size of innovating firms is likely exogenous to researchers' labor supply. To ensure stationarity, we take the first difference of the log of both instrumental variables.

Column (1) of Table 2 presents estimation results for the full sample. A 1% increase in the market value of patents within a research field corresponds to a 0.14% rise in research labor supply. This elasticity is notably lower than those reported for broader occupations. For instance, Arcidiacono et al. (2020) find that a 1% increase in expected earnings raises the subjective probability of choosing an occupation by 0.74%, based on a survey of undergraduate students.

Table 2: The market value of patents and the number of inventors: panel estimation

	(1)	(2)	(3)
Periods	1970-2019	1970-1995	1996-2019
$\Delta ln\left(W_{k,t}\right)$	0.14***	0.17***	0.07***
	(0.01)	(0.01)	(0.01)
Research field FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Observations	5,770	2,721	3,049

Note: The data span 1970-2019 on a yearly basis. The dependent variable is the log change in researcher supply, while the independent variable is the log change in the expected value of patent applications. The instrumental variables are the log changes in unadjusted average patent value and the average size of innovating firms.

This lower elasticity is intuitive, as shifting to a new research field requires significant time, training, and expertise. Our findings align with those of Myers (2020), who shows that scientists exhibit low willingness to alter their research direction in response to higher funding.

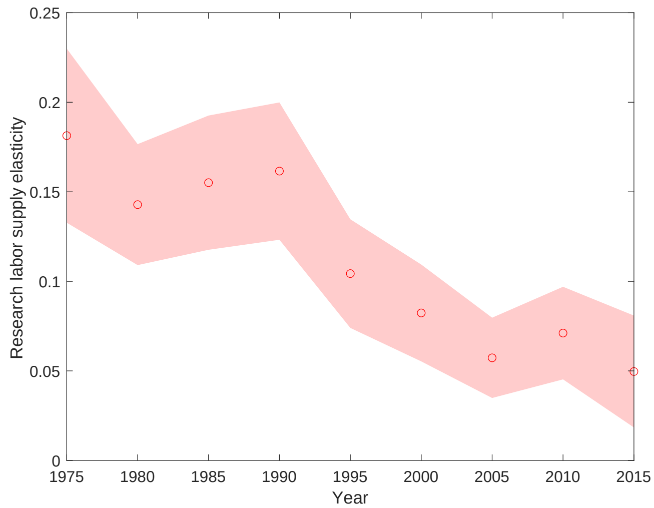
Fact 2: The elasticity of research labor supply is decreasing over time

To examine how the elasticity of researchers' labor supply evolves, we estimate equation (17) separately for periods before and after 1995, the midpoint of our sample. Columns (2) and (3) of Table 2 report the results. The coefficient on $\ln\left(W_{k,t}\right)$ is 0.17 for the pre-1995 period, slightly higher than the full-sample estimate (0.14). In contrast, for 1996-2019, the estimate falls to 0.07.

At a finer level, Figure 3 plots point estimates of research labor supply elasticities from 1975 to 2015, with 95% confidence intervals, using 10-year rolling windows. Consistent with Table 2, research labor supply has become increasingly inelastic in recent decades.[12]

[12] The 10-year windows are $[1970, 1984]$, $[1985, 1994]$, $\ldots$, $[2010, 2019]$.

Figure 3: Research labor supply elasticity has been declining



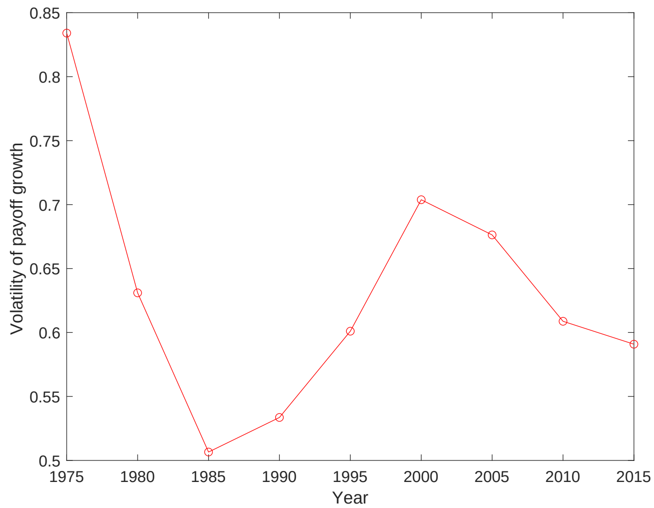
Note: Point estimates of η from 1975 to 2015 with 95% confidence intervals, estimated using 10-year rolling windows.

Why is η declining? One possibility is that the persistence of expected research payoffs –reflecting "technology life cycles" (Abernathy et al., 1978)– has weakened, discouraging investment in specialized knowledge. To test this, we compute the standard deviation of $\Delta \ln(W_{k,t})$ within 10-year rolling windows for each field k and average them to construct an aggregate volatility index, vol_t. If technology cycles were less persistent, we would expect vol_t to trend upward. However, Figure 4 shows no such trend. Instead, volatility has declined, except during 1985-2000, partly aligning with the dot-com bubble.

An alternative explanation is the increasing specialization of research fields, which raises the short-run costs of switching between them. Technological advancements have made discovery tools and methodologies more complex, requiring greater specialization to drive innovation. Additionally, solving multifaceted problems often necessitates collaboration across fields, making researcher networks more critical. Since these networks take time to develop, they introduce an additional entry barrier, further reducing the elasticity of researcher supply.

Short-run elasticity vs. long-run elasticity. By differencing research labor supply and expected payoffs while controlling for research field fixed effects, our empirical design in equation (17) estimates the short-run elasticity of research labor supply. Results in Table 2 and Figure 3 show, for instance, that a doubling of expected payoffs in mRNA vaccine research

Figure 4: Volatility of research payoff growth



Note: Standard deviation of research payoff growth rate, estimated with 10-year rolling windows.

(driven by its surging market value during the Covid-19 pandemic) would attract 14% more researchers compared to the previous year, holding average expected payoff growth in other fields constant (via time fixed effects). The low short-run elasticity of research labor supply may reflect short-term barriers to entering new fields due to increasing knowledge specialization.

These estimates differ from the long-run elasticity, which reflects persistent differences in research labor supply across fields due to sustained gaps in expected payoffs. For example, how many more researchers have entered artificial intelligence over the past decade, given its consistently higher payoffs relative to other fields?

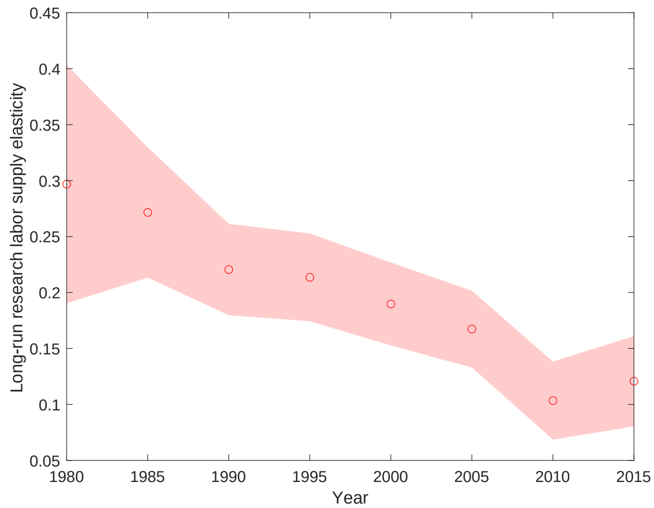
To assess the long-run elasticity of research labor supply and its trend, we estimate the following panel regression for each 10-year window from 1980 to 2015:

$$\Delta_{10} \ln\left(L_{k,t}\right) = \alpha_d^l + \eta_d^l \Delta_{10} \ln\left(W_{k,t}\right) + \chi_t + \gamma_k + \epsilon_{k,t}^l, \; d \in \{1980, 1985, \ldots, 2015\}. \tag{18}$$

Here, $\Delta_{10} \ln\left(L_{k,t}\right)$ and $\Delta_{10} \ln\left(W_{k,t}\right)$ denote the 10-year growth rates of research labor supply and expected monetary payoff to research, respectively. As in regression (17), we instrument $\Delta_{10} \ln\left(W_{k,t}\right)$ using the 10-year growth rates of the average unadjusted patent value ($\widehat{W}_{k,t}$) and the average real output of innovating firms ($\widehat{Y}_{k,t}$).

Figure 5 shows point estimates (circle markers) of the long-run elasticity of research labor supply from 1980 to 2015, with 95% confidence intervals (shaded area). Two key findings emerge.

Figure 5: Long-run research supply elasticity has been declining



Note: Point estimates of long-run research labor supply elasticity (circle marker) from 1980 to 2015 with the 95% confidence intervals (shaded area), estimated with 10-year rolling windows.

First, long-run elasticity has declined, mirroring the short-run trend. Second, long-run elasticities (0.12-0.3) exceed short-run elasticities (0.05-0.18), as learning barriers are lower over time. While a biologist cannot shift to computer science in a year, an undergraduate in biology can do so in graduate school if the expected payoff justifies it.

Fact 3: The elasticity of research labor supply is heterogeneous

The elasticity of research labor supply may vary across fields. Some fields are more accessible, allowing new entrants to quickly master frontier knowledge and innovate, leading to high labor supply elasticity. In contrast, fields with steep learning curves or highly specialized knowledge favor incumbents, making entry more difficult and resulting in a lower elasticity of labor supply, particularly in the short run.

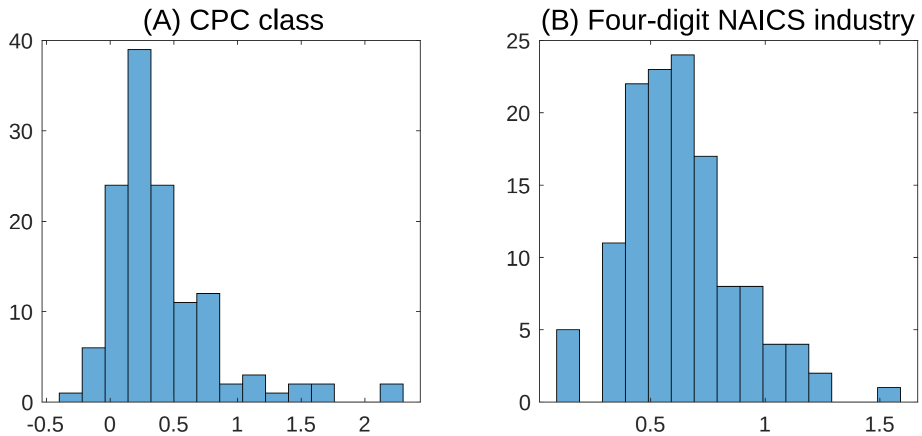
To quantify the field-specific elasticity of research labor supply, we estimate the regression for each of 127 research fields:

$$\Delta \ln \left(N_{k,t}\right) = \alpha_k + \eta_k \Delta \ln \left(W_{k,t}\right) + \epsilon_{k,t},$$

where η_k, our coefficient of interest, measures the elasticity of research labor supply in field k. Consistent with our previous analysis, we instrument $\Delta \ln \left(W_{k,t}\right)$ using log changes in the unadjusted average patent value and the average size of innovating firms.

Panel (A) of Figure 6 presents the distribution of η_k across 129 CPC classes, highlighting substantial variation in η_k across fields.[13] For instance, Electronic Circuitry exhibits the highest elasticity at $\eta_k = 2.27$, while Static Stores has the lowest positive elasticity at $\eta_k = 0.016$. A few fields show negative elasticities, likely due to measurement errors.

Figure 6: Estimates for the elasticities of the labor supply of researchers across fields and industries



Panel (A) estimates across fields (CPC classification); Panel (B) estimates across industries (four-digit NAICS industry classification). x-axis: estimates of η_k, y-axis: frequency.

Industries vary in their exposure to research fields. For example, patents filed by firms in Nursing and Residential Care Facilities (a four-digit NAICS industry) are predominantly in Organic Chemistry. These differences imply that research labor supply elasticities also vary across industries. We define industry j's research labor supply elasticity as $\eta_j = \sum_k \omega_{j,k}\eta_k$, where $\omega_{j,k}$ represents industry j's exposure to research field k, measured as the fraction of its patents belonging to field k, ensuring $\sum_k \omega_{j,k} = 1$.[14] Panel (B) of Figure 6 displays the distribution of η_j across 297 four-digit NAICS industries, revealing substantial variation in research labor supply elasticity across industries.

Analogously, we estimate the long-run field-specific elasticity of research labor supply, η_k^l, with the regression:

$$\Delta_{10} \ln(N_{k,t}) = \alpha_k^l + \eta_k^l \Delta_{10} \ln(W_{k,t}) + \epsilon_{k,t},$$

and compute the long-run industry-specific elasticity of research labor supply $\eta_j^l = \sum_k \omega_{j,k}\eta_k^l$.

[13]For 3 out of 132 CPC classes, elasticities could not be estimated due to insufficient observations.

[14]An alternative approach assigns weights using textual analysis of patent documents to assess industries' technological components, as in Goldschlag et al. (2020).

Column (1) of Table 3 shows that long-run elasticities are positively correlated with short-run elasticities across fields, though the correlation is modest, ($R^2 = 0.1$). This weak relationship may stem from differences in entry barriers across time horizons. Column (2) indicates that long-run elasticities are weakly and negatively correlated with short-run elasticities across industries. As we will show later, only short-run elasticities influence incumbent firms' strategic R&D decisions.

Table 3: Long-run vs. short-run elasticities

	(1)	(2)
Dependent variables	Short-run field elasticity	Short-run industry elasticity
Long-run field elasticity	0.20***	
	(0.05)	
Long-run industry elasticity		-0.08*
		(0.05)
Adj R-squared	0.10	0.01
Observations	129	297

The dependent variables are the short-run field- and industry-specific elasticities of research labor supply. The independent variables are their corresponding long-run elasticities.

Alternative measurement of researchers' labor supply and payoff. An alternative measure of innovators' labor supply is employment in research occupations, which we link to payoffs using the BLS Occupational Employment Survey (OES). This dataset provides annual employment and wage data at the 3-digit NAICS industry and detailed occupation levels since 2001. Research occupations include Computer and Mathematical Occupations (15-0000) and Life, Physical, and Social Science Occupations (19-0000). Unlike inventors, who can work in any occupation, research occupation workers may not produce patents (e.g., they may publish academic papers). While inventors are the closest empirical counterpart to researchers in our model, research occupation data serve as a complementary measure.

We estimate the labor supply elasticity for any occupation group Ω using:

$$\Delta \ln \left(emp_{i,j,t}\right) = \alpha + \eta \Delta \ln \left(w_{i,j,t}\right) + \chi_t + \gamma_i + \kappa_j + \epsilon_{i,j,t}, \tag{19}$$

where $i \in \Omega$, and the dependent variable is the employment growth rate for occupation i in industry j. The key independent variable is the real wage growth rate.

Using current wages ($w_{i,j,t}$) offers greater accuracy and avoids assumptions about stock market efficiency. However, wages capture only a fraction of the total payoff ($W_{i,j,t}$), which also includes future wages and non-wage components such as bonuses and promotions.

To address endogeneity from exogenous shifts in the labor supply curve, we instrument wage growth using a Bartik instrument (Bartik, 1991; Blanchard and Katz, 1992), constructed as:

$$\Delta \widehat{\ln(w_{j,t})} = \sum_{p} s_{j,p} \cdot \Delta \ln(w_{p,t}),$$

where $s_{j,p}$ denotes industry j's employment share in state p in 2000, capturing its initial geographical distribution and predetermined exposure to regional income growth. The variable $\Delta \ln(w_{p,t})$ is the growth rate of real personal income per capita in state p, shaped by sectoral and occupational wage growth, demographic trends, migration, and living cost changes. The motivation for this instrument is that neither $s_{j,p}$ nor $\Delta \ln(w_{p,t})$ is likely to be significantly influenced by exogenous changes in the employment growth of any specific occupation-industry cell.

Table 4: The labor supply and wage for research and non-research occupations

	(1)	(2)	(3)
Occupations	All	Research occupations	Non-research occupations
$\Delta ln\left(w_{j,t}\right)$	19.35***	2.57	20.36***
	(5.91)	(2.46)	(6.56)
Industry FE	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Observations	322,498	2,031	320,467

The data span 1970-2019 with yearly observations. The dependent variable is the log change in the number of employees. The independent variable is the log change in the mean annual wage. The instrumental variable is a Bartik instrument based on the geographical exposure of the industries in 2000.

Column (1) of Table 4 shows that a 1% increase in occupation-industry-specific wage growth corresponds to a 19.35% rise in employment growth. Column (2) reports results for research occupations, where the wage growth coefficient is smaller and not statistically significant. Column (3) shows that for non-research occupations, the estimate is statistically significant and exceeds the full-sample estimate. These findings suggest that research labor supply is considerably more inelastic than that of non-research occupations.

A key limitation of using current wages to measure the payoff is the omission of future wages and non-wage compensation. This makes the estimated elasticity sensitive to wage rigidity and payment structures. This issue is particularly relevant when examining cross-industry variations in research labor supply elasticities, as industries differ in compensation schemes.

Therefore, in the next section, we use research labor supply elasticities estimated from inventor data to test the paper's main mechanism.

5 The effects of R&D by incumbent firms

This section establishes three key facts about the impact of incumbent firms' R&D on firm entry and industry TFP. First, incumbent R&D spending deters new firm entry within the same industry. Second, higher R&D investment slows sectoral productivity growth. Third, R&D extends a firm's lifespan by increasing productivity and limiting competition. These effects are stronger in industries with low research labor supply elasticity. Since these findings align with our model's predictions, we interpret them as evidence supporting the empirical relevance of defensive hiring.

We use three datasets to assess the impact of incumbent firms' R&D on firm entry and firm- and industry-level TFP. Our primary firm-level dataset, Compustat Fundamental Annual, tracks listed firms' sales, profits, employment, and R&D expenditures from 1950 to 2021. We focus on domestic firms, excluding international and multinational companies with at least one foreign segment. For domestic firms, we set negative R&D expenditures to zero, winsorize the top 1% of the R&D distribution, and add one unit to all expenditures to preserve firms with zero R&D when taking logarithms.

We obtain sectoral TFP data from the Bureau of Labor Statistics (BLS), which provides annual series from 1987 to 2019 for 90 four-digit NAICS industries, primarily in manufacturing (e.g., Plastics Product Manufacturing).

For firm entry, we use the Business Dynamics Statistics (BDS) dataset from the US Census Bureau, which reports firm counts by age group (0 to 26+ years) at the industry level. This dataset spans 281 four-digit NAICS industries from 1978 to 2019. We classify zero-age firms as new entrants and compute the entry rate as their share of total firms.

Fact 4. Incumbent R&D negatively predicts firm entry for industries with inelastic research labor supply

First, we examine the relationship between incumbent R&D and new firm entry by estimating the following regression at the four-digit NAICS industry level:

$$Entry_{j,t+5} = \alpha + \beta R\&D_{j,t} + \gamma_j + \chi_t + \epsilon_{i,j,t}, \tag{20}$$

where the dependent variable, $Entry_{j,t+5}$, is industry j's average entry rate from $t+1$ to $t+5$, measured as the share of newly created firms among all firms in the BDS dataset. The key independent variable, $R\&D_{j,t}$, is the logarithm of total R&D expenditure by incumbent firms in industry j. Industry and year fixed effects, γ_j and χ_t, control for unobserved heterogeneity.

Column (1) of Table 5 reports the estimation result: a 1% increase in incumbent firms' R&D predicts a 0.76 percentage point decline in firm entry within the same industry over the next five years –an economically significant effect.

Table 5: Incumbent R&D expenditure and firm entry: panel estimation

	(1)	(2)	(3)	(4)
Dependent variable	Entry rate (t+5), BDS		Listing rate (t+5), Compustat	
$R\&D_{j,t}$	-0.76***	-1.68***	-0.66***	-1.26***
	(0.07)	(0.13)	(0.08)	(0.14)
$R\&D_{j,t} \times \eta_j$		1.80***		1.08***
		(0.13)		(0.22)
Industry FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Adj R-squared	0.82	0.83	0.61	0.62
Observations	1,339	1,339	1,696	1,677

The data span 1970-2019 with yearly observations. The dependent variable is the average entry rate over the next five years. The key independent variables are the average R&D expenditure of incumbent firms ($R\&D$) and the research labor supply elasticity (η).

Next, we examine how research labor supply elasticity moderates the impact of incumbent firms' R&D on firm entry by including an interaction term, $R\&D_{j,t} \times \eta_j$, in the regression. Column (2) presents the results. The positive coefficient on the interaction term suggests that the negative relationship between incumbent R&D and firm entry is stronger in industries with inelastic research labor supply (i.e., low η_j). For instance, a 1% increase in incumbent R&D spending predicts a 2.45% decline in firm entry over the next five years when research labor supply is fully inelastic ($\eta_j = 0$). Conversely, in industries with high η_j, the relationship weakens or even turns positive.

A key concern with including the interaction term is that the industry-specific elasticity of research labor supply (η_j) may correlate with other industry characteristics, such as size. In this case, the positive coefficient on $R\&D_{j,t} \times \eta_j$ could reflect differences in the effect of incumbent R&D on firm entry across these characteristics rather than labor supply elasticity.

Table 6: Research supply elasticity and industry characteristics: cross-sectional analysis

	(1)	(2)	(3)	(4)	(5)
Dep var	Value-added	Research emp share	Wage	Employment	HHI
η_j	-0.64	-0.17	-0.21	0.09	-131.10
	(1.09)	(0.84)	(0.16)	(0.68)	(131.58)
Observations	49	79	79	79	65

The dependent variables are the value-added to GDP ratio, the employment share of research-related occupations, the log of industry average wage, the log of industry employment, and the Herfindahl-Hirschman Index. The variable η_j is the elasticity of research labor supply.

To address this concern, we regress industry characteristics on η_j. These characteristics include the industry value-added to GDP ratio (measuring size), the employment share of research-related occupations (researcher supply), log industry average wage (proxy for technology level), log industry employment (labor market scale), and the Herfindahl-Hirschman Index (HHI) (industry concentration). Table 6 shows that none of these controls are significantly correlated with η_j, suggesting that the positive coefficient on $R\&D_{j,t} \times \eta_j$ is unlikely driven by industry characteristics.[15]

Finally, we examine whether incumbent R&D negatively correlates with the industry's listing rate –the probability that an unlisted firm goes public, reflecting growth opportunities for younger, smaller firms. To test this, we replace the dependent variable in equation (20) with the five-year average listing rate (new listings as a share of total listings).

Columns (3) and (4) of Table 5 show that high incumbent R&D predicts a lower listing rate. This effect is stronger in industries with an inelastic research labor supply, as indicated by the positive coefficient on the interaction term. These findings suggest that incumbent R&D spending hinders competitors from becoming publicly traded, particularly in industries where research labor supply is inelastic.[16]

[15]While η_j could, in principle, influence industry characteristics such as researcher supply and concentration, these factors are largely shaped by technological intensity and entry barriers. Thus, their observed correlation with η_j is insignificant.

[16]As a robustness check, Table A.1 in Appendix A confirms that the results remain significant when using entry and listing rates over the next one and three years as alternative dependent variables.

Fact 5. R&D by the incumbent negatively predicts productivity growth for industries with inelastic research labor supply

Next, we show that incumbent R&D negatively affects the productivity growth of other firms in the same industry, particularly in industries with a low elasticity of research labor supply.

We measure the spillover effect of listed companies' R&D on the productivity growth of other listed firms in the same industry by estimating the firm-level regression:

$$\Delta z_{-i,j,t+5} = \alpha + \beta R\&D_{i,j,t} + \gamma_j + \chi_t + \epsilon_{i,j,t}, \tag{21}$$

where the key independent variable, $R\&D_{i,j,t}$, is the logarithm of R&D expenditure for listed company i. The dependent variable, $\Delta z_{-i,j,t+5}$, represents the labor productivity growth of all other listed firms in industry j from t to $t+5$.

The average labor productivity of listed firms in industry j, excluding company i, is calculated as:

$$z_{-i,j,t} = \frac{\sum_{i' \in \Psi_{j,t} \backslash i} y_{i',j,t}}{\sum_{i' \in \Psi_{j,t} \backslash i} l_{i',j,t}},$$

where $\Psi_{j,t} \backslash i$ is the set of listed firms in industry j with employment data, excluding firm i. Here, $y_{i',j,t}$ and $l_{i',j,t}$ denote company sales and employment, respectively. Consequently, $\Delta z_{-i,j,t+5}$ is computed as $(z_{-i,j,t+5}/z_{-i,j,t} - 1)/5$.

Column (1) of Table 7 shows that a listed company's R&D expenditure is negatively correlated with labor productivity growth in other listed firms within the same industry. This relationship arises from two opposing forces. On one hand, R&D reduces researcher availability, limiting productivity growth when labor supply is scarce. On the other hand, R&D fosters productivity through knowledge spillovers, especially among technologically proximate firms (Bloom et al., 2013; Fernández-Villaverde et al., 2024). However, the negative spillover effect prevails.

Next, we show that this negative effect is particularly pronounced in industries with an inelastic research labor supply. Specifically, we examine how research labor supply elasticity moderates the spillover effect of firms' R&D on other firms' productivity growth by including an interaction term, $\eta_j \times R\&D_{i,j,t}$, in the regression. This term captures how a firm's R&D and research labor supply elasticity jointly influence the productivity of other listed firms.

The positive interaction term in Column (2) of Table 7 indicates that a firm's R&D exerts a

Table 7: Incumbent R&D expenditure and sectoral productivity: panel

	(1)	(2)	(3)	(4)
Dependent variable	$\Delta z_{-i,j,t+5}$		$\Delta z_{j,t+5}$	
$R\&D_{i,j,t}$	-0.09*	-0.24**		
	(0.05)	(0.10)		
$R\&D_{i,j,t} \times \eta_j$		0.22*		
		(0.13)		
$R\&D_{j,t}$			-0.01*	-0.03***
			(0.004)	(0.01)
$R\&D_{j,t} \times \eta_j$				0.03**
				(0.01)
Industry FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Adj R-squared	0.14	0.14	0.56	0.56
Observations	39,299	39,271	589	589

The data span 1970-2019 with yearly observations. The dependent variable is the productivity growth rate (percentage points). The key independent variables are R&D expenditure ($R\&D$) and research labor supply elasticity (η).

stronger negative spillover on other firms' productivity growth in industries with a low elasticity of research labor supply. A 1% increase in a listed company's R&D spending corresponds to a 0.24% decline in labor productivity growth for other listed firms when research labor supply is fully inelastic ($\eta_j = 0$), a stronger effect than the unconditional estimate in Column (1).

Since incumbent R&D negatively predicts both the productivity growth of other incumbents and firm entry in industries with an inelastic research labor supply, it follows naturally that incumbent R&D should also negatively predict industry TFP growth in such industries.

To test this hypothesis, we use four-digit NAICS industry-level data to estimate the regression:

$$\Delta z_{j,t+5} = a + bR\&D_{j,t} + c\eta_j \times R\&D_{j,t} + \gamma_j + \chi_t + \epsilon_{j,t}, \tag{22}$$

where the dependent variable, $\Delta z_{j,t+5}$, represents industry j's yearly TFP growth from t to $t+5$, as constructed by the BLS. The key independent variable, $R\&D_{j,t}$, is the logarithm of total R&D expenditure by listed companies in industry j.

Column (3) of Table 7 shows that listed companies' R&D expenditure negatively predicts industry TFP growth, with a 1% increase in R&D spending associated with a 0.01 percentage point decline in yearly TFP growth over the next five years. Column (4) further indicates that this negative relationship is significantly stronger in industries with inelastic research labor supply.

Specifically, when $\eta_j = 0$, a 1% increase in R&D spending corresponds to a 0.03 percentage point decline in yearly TFP growth –three times the unconditional estimate in Column (3).

At first glance, this result may seem to contradict the view that R&D drives economic growth. However, two factors clarify this interpretation. First, our regression omits positive R&D spillover effects *across* industries, which play a crucial role in growth (Cai and Li, 2019). Second, industry fixed effects remove the stable, positive R&D-productivity growth relationship across industries. Notably, excluding these fixed effects turns the R&D coefficient positive, consistent with Jones and Williams (1998, ft. 14, p. 1131), who find that the R&D-productivity link depends on long-run cross-industry comovement.

Table A.2 in Appendix A shows that incumbent R&D expenditure is not significantly related to productivity growth over one- or three-year horizons. This aligns with the notion that creative destruction and innovation require time to meaningfully impact measured productivity (Brynjolfsson et al., 2021).

Fact 6. Incumbent R&D increases the lifespan of the incumbent firms in industries with inelastic research labor supply

Given the adverse impact of incumbent R&D on competitor entry, public listing, and productivity growth, it follows that R&D likely extends incumbents' lifespan –a primary concern and key motivation for defensive hiring.

We test this hypothesis by estimating the following cross-sectional regression:

$$LifeExp_{i,j} = \alpha + \beta R\&D_{i,j} + Rvn_{i,j} + \gamma_j + Birth_{i,j} + \epsilon_{i,j}, \tag{23}$$

where the dependent variable, $LifeExp_{i,j}$, represents the lifespan of listed company i in industry j, measured as the number of years between its listing and delisting. The key independent variable, $R\&D_{i,j}$, is the logarithm of company i's average R&D expenditure. To ensure comparability among firms within the same industry and listing year, we control for industry fixed effects, γ_j, and listing year fixed effects, $Birth_{i,j}$. To align with our research labor elasticity measure, we restrict the sample to firms listed after 1970 (the start of our patent data) and delisted before 2019 (its endpoint).

Column (1) of Table 8 shows that increasing a company's R&D expenditure by 10% is associated with a 0.067-year (0.1×0.67) increase in lifespan. This association may suggest that

R&D investments enhance a company's competitiveness and help mitigate challenges from potential competitors. Alternatively, it could be that more competitive companies tend to allocate more resources to R&D and also enjoy longer lifespans as a result of their initial competitiveness.

Column (2) of Table 8 presents results with the interaction term $\eta_j \times R\&D_{i,j}$. The negative coefficient suggests that R&D has a stronger association with firm lifespan in industries with a lower elasticity of research labor supply and a weaker association in industries with higher elasticity. This finding aligns with the causal effect of R&D on lifespan. Intuitively, in industries with an inelastic research labor supply, incumbents can more effectively leverage monopsony power to shield themselves from creative destruction. Using the previous calculation, in an industry with a completely inelastic research labor supply ($\eta_j = 0$), a 10% increase in R&D expenditure extends a firm's lifespan by 0.083 years.

Table 8: Incumbent R&D expenditure and lifespan of the incumbent firm: cross-sectional analysis

	(1)	(2)
Dependent variable	Lifespan	
$R\&D_{i,j}$	0.67***	0.83***
	(0.04)	(0.13)
$R\&D_{i,j} \times \eta_j$		-0.24**
		(0.21)
Industry FE	Yes	Yes
Cohort FE	Yes	Yes
Adj R-squared	0.41	0.41
Observations	7,429	7,392

The data span 1970-2019 with yearly observations. The dependent variable is the incumbent firms' lifespan. The key independent variables include the logarithm of average R&D expenditure (*R&D*), research labor supply elasticity (η), and the logarithm of average revenues from sales (*Revenue*).

Finally, Tables A.3-A.5 in Appendix A show that Facts 4-6 do not hold for long-run research labor supply elasticities. Specifically, the interaction term between long-run labor supply elasticity and incumbent R&D ($\eta_j^l \times R\&D_{j,t}$) is not statistically significant. This finding will motivate the extension of our quantitative model below to incorporate both margins.

6 Quantitative general equilibrium model

Empirical evidence from the last two sections motivates extending our model into a general equilibrium framework for quantitative analysis and policy evaluation. The key extensions focus on workers. First, we allow occupational choices, making *aggregate* research labor supply endogenous to sectoral wages. Second, researchers can switch sectors at a cost, determining *sectoral* labor supply elasticity endogenously. Third, switches may be immediate or delayed, generating different supply elasticities over time, as observed in the data.

6.1 Environment and occupational choice

The economy consists of J sectors ($j \in \{1, \ldots, J\}$), each producing a distinct intermediate good assembled into homogeneous final goods. A continuum of workers $i \in [0, L]$, where L is total labor supply, choose between two occupations: production (p) or research (r).[17] For simplicity, all workers have homogeneous productivity across occupations.

Consumption of final goods, $C_{i,t}$, equals total income: wage ($w_{i,t}$, which depends on occupation) plus capital income ($\Pi_{i,t}$) from firm ownership. We denote production and R&D wages as w_t^p and w_t^r, respectively.

Workers have heterogeneous occupational preferences. Specifically, worker i's utility is $\log(C_{i,t})$ in production and $\log(C_{i,t} - d_{i,t})$ in research, where $d_{i,t}$ represents worker-specific costs for research, such as training and learning, reducing utility. Workers with higher $d_{i,t}$ prefer production over research. We assume $d_{i,t}$ increases with worker index i and follows:

$$d_{i,t} = w_t^p \cdot (b_1 + b_2 \cdot i/L), \quad b_2 > 0. \tag{24}$$

Scaling $d_{i,t}$ by w_t^p ensures stationarity along the balanced growth path (BGP).

Each period, a threshold $i^*(t)$ determines occupations: workers in $[0, i^*(t)]$ become researchers, while those in $(i^*(t), L]$ enter production. The total number of researchers is $N_t^r = i^*(t)$ and the total number of production workers is $N_t^p = L - i^*(t)$.

Workers at the threshold are indifferent between occupations, equating utilities:

$$\log\left(w_t^p + \Pi_{i^*(t),t}\right) = \log\left(w_t^r + \Pi_{i^*(t),t} - d_{i^*(t),t}\right). \tag{25}$$

The left-hand side represents the utility of a worker choosing production, while the right-hand side represents utility in research. This implies $d_{i^*(t),t} = w_t^r - w_t^p$, or using equation (24):

$$w_t^p \cdot (b_1 + b_2 \cdot i^*(t)/L) = w_t^r - w_t^p.$$

[17] Population is fixed, and relaxing this assumption does not affect the results.

Substituting $i^*(t) = N_t^r$ gives:

$$\frac{N_t^r}{L} = \frac{1}{b_2}\left(\frac{w_t^r - w_t^p}{w_t^p}\right) - \frac{b_1}{b_2}, \tag{26}$$

that is, the researcher share N_t^r/L rises with the wage premium $(w_t^r - w_t^p)/w_t^p$. The slope $1/b_2$ determines the elasticity of the aggregate research labor supply, while the intercept $-b_1/b_2$ sets its steady-state level. At the end of each period, workers separate from jobs and choose occupations *ex novo*.

6.2 The allocation of researchers

After workers make their occupational choices, researchers are randomly and evenly distributed across the J sectors. This results in an initial sectoral research labor supply of $n_{j,t}^r = n_t^r \equiv n_t^r$ in each sector j. In the symmetric equilibrium, wages are equalized across sectors, such that $w_{j,t}^r = w_t^r$, ensuring that researchers have no incentive to move between sectors.

Next, we derive the sectoral labor supply for researchers. To do this, we allow sector j to deviate from the homogeneous research wage w_t^r by setting $w_{j,t}^r \neq w_t^r$, while other sectors maintain $w_{-j,t}^r = w_t^r$. Although this deviation would not occur in a symmetric equilibrium, it is crucial to understand the impact on sectoral research labor supply, as it plays a significant role in the incumbent firms' wage and hiring decisions.

The wage differential between sector j and the other sectors incentivizes researchers to move from lower- to higher-paying sectors. However, switching sectors incurs a cost, which determines the extent of the sectoral reallocation of researchers.

Following Alvarez and Shimer (2011), we call researchers who switch to another sector "switchers." We denote with m_t the measure of potential job switchers:

$$m_t = \begin{cases} n_t^r, & \text{if } w_{j,t}^r < w_t^r, \\ (J-1)n_t^r, & \text{if } w_{j,t}^r > w_t^r. \end{cases}$$

In the first case, researchers in sector j (with a measure of n_t^r), where the wage is lower, are the potential switchers. In the second case, researchers in the other sectors (with a measure of $(J-1)n_t^r$) become the potential switchers.

These potential job switchers randomly draw a switching cost from the *i.i.d.* uniform distribution $\mathcal{U}(0, \xi_t)$, where ξ_t is the maximum switching cost, determined by $\xi_t = \overline{\xi} w_t^r m_t / n_t^r$, where $\bar{\xi}$ is a parameter that scales the switching cost. A higher $\bar{\xi}$ makes job switching costlier and implies a lower measure of job switchers, consequently reducing the elasticity of the labor supply for researchers. We scale the switching cost with w_t^r to preserve stationarity in the BGP. Consistent with the standard assumption of convex adjustment costs, implying that the marginal adjustment cost increases in the level of adjustment, we assume that the job switching costs are proportional to the share of potential job switchers in research labor in each sector, captured by the term m_t/n_t^r.

Potential switchers with switching costs below the expected wage increase will choose to switch. If a researcher pays the cost, the transition occurs with probability q in the current period and $1-q$ in the next. We refer to the former as short-run switchers and the latter as long-run switchers. The measure of switchers to sector j, denoted $\widehat{m}_{j,t}$, is given by:

$$\widehat{m}_{j,t} = \frac{(w_{j,t}^r/w_t^r - 1)n_t^r}{\bar{\xi}}. \tag{27}$$

This measure is positive (negative) if $w_{j,t} > w_t$ ($w_{j,t} < w_t$). Its absolute value increases with the wage gap between sector j and the other sectors and decreases with ξ. Appendix C provides the full derivation of equation (27). Among switchers, a measure of $q\widehat{m}_{j,t}$ arrives in t, while $(1-q)\widehat{m}_{j,t}$ arrives in $t+1$.

The labor supply for research workers in sector j is the sum of the initial research labor supply n_t^r and the inflow of short-run switchers, $q\widehat{m}_{j,t}$, and the inflow of long-run switchers who move based on decisions made at $t-1$, $(1-q)\widehat{m}_{j,t-1}$: $L_{j,t} = n_t^r + q\widehat{m}_{j,t} + (1-q)\widehat{m}_{j,t-1}$, which can be rewritten to the more familiar form:

$$\frac{L_{j,t} - n_t^r}{n_t^r} = \overbrace{\frac{1}{\xi}\left(\frac{w_{j,t}^r - w_t^r}{w_t^r}\right)}^{\text{Short-run switchers}} + \overbrace{\frac{(1-q)}{q\xi}\frac{n_{t-1}^r}{n_t^r}\left(\frac{w_{j,t-1}^r - w_{t-1}^r}{w_{t-1}^r}\right)}^{\text{Long-run switchers}}, \tag{28}$$

where $\xi = \bar{\xi}/q$. The detailed derivation of equation (28) is provided in Appendix C. The first term on the right-hand side of equation (28) represents short-term switchers who move to sector j based on decisions made at t. The second term represents long-term switchers who move based on decisions made at $t-1$.[18] Equation (28) shows that the short-run elasticity of the sectoral research labor supply is $1/\xi$ around the symmetric equilibrium (i.e., $w_{j,t}^r = w_t^r$ and $L(w_{j,t}^r) = n_t^r$),

[18] We ignore researchers who qualify as both long-run (with sufficiently low $\xi_{i,t}$) and short-run switchers (with sufficiently low $\xi_{i,t+1}$), as their measure is negligible.

and it is the theoretical counterpart of the parameter η in our empirical analysis (see equation 17). Long-run elasticity is $1/(q\xi)$, and it is the theoretical counterpart of the parameter η^l (see equation 18).[19] Long-run elasticity exceeds short-run elasticity. Both decrease as switching costs (ξ) rise. Given the same ξ, long-run elasticity decreases as the fraction of short-run switchers (q) increases.

6.3 The production sectors

Final goods are produced competitively using intermediate inputs, according to the production function:

$$\ln(Y_t) = \frac{1}{J}\sum_{j=1}^{J} \ln(Y_{j,t}),$$

where $Y_{j,t}$ is the intermediate input from sector j. Since the model omits investment, and R&D forgoes using final goods, consumption is equal to output: $C_t = Y_t$.

Profit maximization for the representative final-goods producer implies the demand function for the intermediate input j, $Y_{j,t} = \frac{Y_t P_t}{P_{j,t}}$, where $P_{j,t}$ is the price of intermediate good j charged by the monopolist producer in sector j, and P_t is the price of final goods, which is our numeraire.

Each sector j comprises an incumbent firm and a continuum of potential entrants that employ researchers to innovate. The incumbent produces intermediate good j according to the linear production technology $Y_{j,t} = A_{j,t} L_{j,t}$, where $A_{j,t}$ is sectoral productivity and $L_{j,t}$ is the labor input of production workers in sector j.

Sectoral productivity improves with innovation according to the law of motion:

$$A_{j,t} = \begin{cases} \gamma \overline{A}_{t-1}, & \text{with probability } f_{j,I,t} + f_{j,E,t}, \\ \overline{A}_{t-1}, & \text{with probability } 1 - f_{j,I,t} - f_{j,E,t}, \end{cases} \tag{29}$$

where $\gamma > 1$ is the improvement in the quality of output consequent to the successful innovation, $f_{j,I,t}$ and $f_{j,E,t}$ are the incumbent's and entrants' innovation probabilities, respectively, and $\overline{A}_{t-1}$ is the common technological frontier of the economy at the end of period $t-1$, defined by the highest technology across sectors $\overline{A}_{t-1} = \max_j A_{j,t-1}$, which can either be enhanced by the innovation undertaken by either the incumbent or the entrants or remain the same if the

[19] The derivation of the model-implied elasticities are provided in Appendix C.

innovation is unsuccessful:

$$\overline{A}_t = \begin{cases} \gamma \overline{A}_{t-1} & \text{with probability } 1 - \prod_{j=1}^{J} \left(1 - f_{j,I,t} - f_{j,E,t}\right), \\ \overline{A}_{t-1} & \text{with probability } \prod_{j=1}^{J} \left(1 - f_{j,I,t} - f_{j,E,t}\right), \end{cases} \tag{30}$$

where $\prod_{j=1}^{J} \left(1 - f_{j,I,t} - f_{j,E,t}\right)$ is the probability of unsuccessful innovation across the different sectors J in period t. Equations (29) and (30) assume that each sector has access to the world technological frontier achieved in the preceding period $t-1$. [20]

In the monopolistic-competitive production market, the incumbent sets the price to maximize profits. The incumbent's operating profit, net of R&D expenditures, is equal to $\pi_{j,t} = \left(P_{j,t} - mc_{j,t}\right) Y_{j,t}$, where the marginal cost $mc_{j,t}$ is equal to $mc_{j,t} = \frac{w_t^p}{A_{j,t}}$, increasing with the production wage (w_t^p) and decreasing with sectoral productivity ($A_{j,t}$). The incumbent faces a competitive fringe of imitators that have access to the technological frontier $\overline{A}_{t-1}$, and produce the intermediate good at a higher marginal cost $\widehat{mc}_{j,t} = \frac{\chi w_t^p}{\overline{A}_{t-1}}$, since $\chi > 1$.

The incumbent sets the price equal to the imitators' marginal cost, $P_{j,t} = \widehat{mc}_{j,t}$, which is uniform across sectors. Thus, all incumbents charge $P_{j,t} = P_t = 1$, implying $Y_{j,t} = Y_t$ and $\widehat{mc}_{j,t} = 1$. This ensures sectoral output is identical, and the production wage is proportional to the technological frontier, $w_t^p = \overline{A}_{t-1}/\chi$. Given w_t^p, the incumbent's marginal cost and operating profit net of R&D expenditures are:

$$mc_{j,t} = \begin{cases} \frac{1}{\gamma\chi} & \text{if innovating,} \\ \frac{1}{\chi} & \text{if not innovating,} \end{cases} \quad \text{and } \pi_{j,t} = \begin{cases} \left(1 - \frac{1}{\gamma\chi}\right) Y_{j,t} & \text{if innovating,} \\ \left(1 - \frac{1}{\chi}\right) Y_{j,t} & \text{if not innovating,} \end{cases}$$

respectively.

6.4 Equilibrium final output

In equilibrium, final output depends on sectoral productivity and the allocation of production workers. By the law of large numbers, productivity is $\gamma \overline{A}_{t-1}$ in the fraction $f_{I,t} + f_{E,t}$ of sectors with successful innovation, and $\overline{A}_{t-1}$ in the remaining sectors. Since all sectors share the same innovation probability, we omit sector indices for brevity. Let $L_{s,t}$ and $L_{u,t}$ denote the allocation of production workers in sectors with successful and unsuccessful innovation, respectively.

[20] This simplifying assumption allows us to abstract from the heterogeneity across sectors consequent to the sectoral stochastic innovations and the delays in the adoption of the latest technology. In this way, the equilibrium is symmetric, with the same wage for researchers across sectors, and we forgo tracking the distance from the technological frontier in each sector.

We solve the model by imposing the condition that output is equal across sectors:

$$\overline{A}_{t-1} L_{s,t} = \gamma \overline{A}_{t-1} L_{u,t} = Y_t, \tag{31}$$

and the labor market for the production workers clears:

$$L_{s,t} \left(f_{I,t} + f_{E,t} \right) + L_{u,t} \left(1 - f_{I,t} - f_{E,t} \right) = N_t^p, \tag{32}$$

where N_t^p is the total measure of production workers.

Using the equilibrium conditions (31)) and (32), final output is equal to:

$$Y_t = \frac{\gamma \overline{A}_{t-1} N_t^p}{\left(f_{I,t} + f_{E,t} \right) \gamma + \left(1 - f_{I,t} - f_{E,t} \right)},$$

which increases with the past technological frontier, the measure of production workers, and the size of the innovation.

6.5 Entry decision

Each sector has a continuum of potential entrants with varying R&D efficiency k, distributed according to the cumulative density function $\Psi(k)$. The total measure of potential entrants is $\psi = \Psi(+\infty)$.

The value of the innovating entrant ($V_{E,j,t}$) is:

$$V_{E,j,t} = \left(1 - \frac{1}{\gamma \chi} \right) Y_{j,t} - \iota Y_{j,t} + \frac{\mathbb{E}_t V_{I,j,t+1}}{1 + r_t},$$

where $(1 - 1/\gamma\chi) Y_{j,t}$ is the entrant's operating profit net of R&D expenditure, and $\iota Y_{j,t}$ represents the fixed entry cost. A higher ι raises entry barriers, deterring new firms. $V_{I,j,t+1}$ is the value of becoming an incumbent upon successful innovation, discounted by the interest rate r_t. The log utility function implies that the interest rate is proportional to consumption growth, as given by the Euler equation, $r_t = -\ln(\beta) + \mathbb{E}_t \Delta \ln(C_{t+1})$, where β is the discount factor.

Each entrant employs a unit measure of researchers, compensated at the equilibrium wage. Entry occurs if the expected value is non-negative. The free-entry condition determines the threshold R&D efficiency required for entry:

$$\underline{k}_{j,t} V_{E,j,t} - w_{j,t}^r = 0, \tag{33}$$

where $\underline{k}_{j,t}$ represents the threshold innovation probability for entrants ensuring non-negative $V_{E,j,t}$. This threshold rises with researcher wages $w_{j,t}^r$ and falls with the value of innovation $V_{E,j,t}$.

The employment of researchers and the probability of successful innovation by entrants are equal to:

$$n_{j,E,t} = \int_{\underline{k}_{j,t}}^{+\infty} 1 d\Psi\left(k\right) = \psi - \Psi(\underline{k}_{j,t}) \quad \text{and} \quad f_{j,E,t} = \int_{\underline{k}_{j,t}}^{+\infty} k d\Psi\left(k\right), \tag{34}$$

respectively. Equations (33) and (34) show that researcher employment and the probability of successful innovation by entrants decline with the threshold R&D efficiency $\underline{k}_{j,t}$ and researcher wages $w^r_{j,t}$.

6.6 Wage setting of the incumbent

The incumbent selects researcher wages $w^r_{j,t}$ and employment $n_{j,I,t}$ to maximize the firm's continuation value, $V_{j,I,t}$:

$$\begin{aligned} V_{j,I,t}(w^r_{j,t-1}) = \max_{w^r_{j,t}} \phi n_{j,I,t} \left(1 - \frac{1}{\gamma\chi}\right) Y_{j,t} + \left(1 - \phi n_{j,I,t} - f_{j,E,t}\right) \left(1 - \frac{1}{\chi}\right) Y_{j,t} \\ - n_{j,I,t} w^r_{j,t} + \left(1 - f_{j,E,t}\right) \frac{\mathbb{E}_t V_{j,I,t+1}(w^r_{j,t})}{1 + r_t}, \end{aligned} \tag{35}$$

subject to the market-clearing condition for researchers in sector j: $n_{j,I,t} + n_{j,E,t} = L(w^r_{j,t})$. Note that in equation (35), the previous period's wage is a state variable because it affects the current research labor supply by influencing long-term switchers from the prior period.

Equation (35) shows that the incumbent's value comprises four elements: (i) the operating profit if innovation succeeds, $(1 - 1/\gamma\chi)Y_{j,t}$, occurring with probability $\phi n_{j,I,t}$, where ϕ is the incumbent's R&D efficiency; (ii) the operating profit if neither the incumbent nor entrants innovate, $(1 - 1/\chi)Y_{j,t}$, occurring with probability $1 - \phi n_{j,I,t} - f_{j,E,t}$; (iii) researcher wage payments, $n_{j,I,t} w^r_{j,t}$; and (iv) the discounted continuation value if new entrants fail to innovate and displace the incumbent, $(1 - f_{j,E,t})V_{j,I,t+1}/(1 + r_t)$.

For simplicity, we assume the incumbent treats $V_{j,I,t+1}$ as exogenous and does not internalize its innovation's effect on the technological frontier, $\overline{A}_t$. This assumption is reasonable since a single firm's innovation has a negligible effect on the economy's technological frontier. The market-clearing condition implies that an increase in researcher wages, $w^r_{j,t}$, raises the sector's labor supply, $L(w^r_{j,t})$, while reducing entrants' employment, $n_{j,E,t}$.

Substituting the labor market-clearing condition into the Bellman equation (35), we obtain the incumbent's first-order condition with respect to the wage:

$$\phi\frac{\partial n_{j,I,t}}{\partial w^r_{j,t}}\Delta\pi_{j,t}+\frac{df_{j,E,t}}{dw^r_{j,t}}\widehat{V}_{j,t}-\frac{\partial n_{j,I,t}}{\partial w^r_{j,t}}w^r_{j,t}-n_{j,I,t}+\left(\frac{1-f_{j,E,t}}{1+r_t}\right)\frac{dE_tV_{j,I,t+1}}{dw^r_{j,t}}=0, \tag{36}$$

where $\Delta\pi_{j,t}=\left(\frac{1}{\chi}-\frac{1}{\gamma\chi}\right)Y_{j,t}$ is the incremental profit from the incumbent's innovation, and $\widehat{V}_{j,t}=(1-1/\chi)Y_{j,t}+\mathbb{E}_tV_{j,I,t+1}/\left(1+r_t\right)$ represents the incumbent's value loss due to creative destruction. The last term on the left-hand side of equation (36) measures the impact of wages on the continuation value by attracting long-term switchers to this sector in the next period, a phenomenon we refer to as the *dynamic attraction effect*.

The dynamic attraction effect is determined by the envelope condition of the Bellman equation (35) with respect to the previous period's wage:

$$\frac{dV_{j,I,t}}{dw^r_{j,t-1}}=\phi\frac{\partial n_{j,I,t}}{\partial w^r_{j,t-1}}\Delta\pi_{j,t}-\frac{\partial n_{j,I,t}}{\partial w^r_{j,t-1}}w^r_{j,t}. \tag{37}$$

This equation has two components: one reflects the effect of the previous wage on the incumbent's current innovation, and the other captures its positive impact on current wage costs.

The sign of the dynamic attraction effect is negative, meaning that a high wage reduces future value, if $\phi\Delta\pi_{j,t}<w^r_{j,t}$ (the wage exceeds the marginal profit return). Moreover, the magnitude of the dynamic attraction effect is proportional to $\partial n_{j,I,t}/\partial w^r_{j,t-1}$, as determined by equation (28):

$$\frac{\partial n_{j,I,t}}{\partial w^r_{j,t-1}}=\frac{\partial L_{j,t}}{\partial w^r_{j,t-1}}=\frac{(1-q)}{q\xi}\frac{n^r_{t-1}}{w^r_{t-1}}, \tag{38}$$

which declines with the share of short-run switchers q. Intuitively, a lower q increases the relevance of long-run switchers, strengthening the dynamic effect on the incumbent's future value.

Forwarding equations (37) and (38) to the next period and substituting them into equation (36) yields:

$$w^r_{j,t}=\overbrace{\phi\Delta\pi_t}^{\text{mpr}}-\frac{\overbrace{n_{j,I,t}}^{\text{monopsony}}-\overbrace{\underline{k}_{j,t}\Psi'\underline{k}'_{j,t}\widehat{V}_t}^{\text{Defensive hiring}}+\overbrace{\Phi_{j,t}\left(w^r_{j,t+1}-\phi\Delta\pi_{j,t+1}\right)}^{\text{Dynamic attraction}}}{\Psi'\underline{k}'_{j,t}+\partial L_{j,t}/\partial w^r_{j,t}}, \tag{39}$$

with $\Phi_{j,t}=\left(\frac{1-f_{j,E,t}}{1+r_t}\right)\frac{(1-q)}{q\xi}\frac{n^r_t}{w^r_t}$. Equation (39) indicates that researcher wages consist of four components: (i) the marginal profit contribution of R&D (mpr), (ii) the "classic monopsony" effect, where higher wages reduce profits, (iii) the "defensive hiring" effect, where higher wages increase survival probability, and (iv) the "dynamic attraction" effect, where higher wages encourage more hiring in the next period by attracting long-run switchers.

Equation (39) shows that defensive hiring is larger when $\widehat{V}_t$ (the value to defend) is high. Moreover, for a given $\widehat{V}_t$, defensive hiring is more common when $n_{j,I,t}$ is low (i.e., a smaller R&D team relative to the researcher pool). This aptly describes top US tech firms: they have large market valuations but they hire a relatively small share of all relevant researchers, suggesting the empirical relevance of our model. The influence of the overall distortions caused by defensive hiring, monopsony power, and dynamic attraction on wages intensifies when the short-run research labor supply is inelastic, i.e., when $\partial L_{j,t}/\partial w^r_{j,t}$ is low.

6.7 Balanced growth path and calibration

To attain the BGP of the system, we detrend the variables by the growing technological frontier, $\overline{A}_{t-1}$. The equilibrium is determined by nine equations governing the nine variables: w^r, $\underline{k}$ (equivalently, f_E), V_I, V_E, N^r (equivalently, n^r, N^p, π, and $\Delta\pi$), n_I (equivalently, f_I), Y (equivalently, C), r, and g. Table D.6 in the Appendix summarizes these equations.

We calibrate the model using annual data from 1970-1995, a period characterized by a relatively high elasticity of researcher labor supply and strong TFP growth, as estimated in Section 4. This period serves as the benchmark for analyzing the effects of changing the elasticity of labor supply and policy shifts on equilibrium. Table 9 summarizes our calibration.

We set the discount factor to 0.973, consistent with a 4% risk-free interest rate and a 1.3% technology growth rate in the BGP, as observed in US data. The number of sectors, J, is set to two.[21] Total population, L, is set to 2, normalizing sectoral population to 1. The imitator marginal cost, $\chi = 1.3$, replicates the US average markup of 1.3 documented by Hall (2018).

Following Kortum (1997), potential entrants' R&D efficiency follows a Pareto distribution, $\Psi(k) = \psi[1-(k_m/k)^{\lambda}]$, where k_m is the lowest R&D efficiency, λ determines distribution shape, and ψ is the entrant measure. We normalize $k_m = 0.1$ since only ψk_m^{λ} is identifiable (we cannot separately identify ψ and k_m). The sector switching cost $\overline{\xi}$ and the probability of short-run switching, q, are set to 3.33 and 0.57, respectively. They jointly match the pre-1995 short-run and

[21] Since all sectors adopt the previous period's technological frontier, BGP growth is approximately $\gamma - 1$ and largely independent of innovation probabilities f_I and f_E when J is large. A low J ensures f_I and f_E remain relevant for growth.

Table 9: Calibration

Panel (A): Parameters externally calibrated		
Parameter	Value	Description
β	0.973	Discount factor
J	2	The number of sectors
L	2	Population
$\overline{\xi}$	3.33	Switching cost
q	0.57	Probability of short-run switching
b_2	1/0.74	Coefficient of disutility of research
χ	1.3	Marginal cost of imitators
Panel (B): Parameters internally calibrated		
Parameter	Value	Description
γ	1.053	Innovation size
λ	1.48	Shape of entrants' R&D efficiency distribution
b_1	0.068	Constant term in the disutility of research
ψ	1.49	Measure of potential entrants in each sector
ι	0.57	Fixed cost to the new entrant

long-run elasticities of research labor supply of 0.17 and 0.3, respectively, as estimated in Section 4.[22] The disutility coefficient of research, $b_2 = 1/0.74$, implies an occupational choice elasticity of 0.74, as estimated by Arcidiacono et al. (2020). We follow standard practice in the literature and assume low R&D efficiency for incumbents, setting $\phi = k_m$. For example, Akcigit and Ates (2021) assume that the entrant R&D efficiency is roughly 100 times that of incumbents.

Table 10: Model fit

Moment	Model	Data
Creative destruction probability	0.13	0.13
Share of research employment	5.5%	5.5%
Research wage premium	12%	12%
Incumbent's share of research employment	48%	48%
Technological growth rate	0.013	0.013

Five parameters are calibrated internally: innovation size (γ), the shape parameter of the Pareto distribution (λ), the constant term in the disutility of research (b_1), the total measure of potential entrants (ψ), and the fixed cost for new entrants (ι). These parameters are calibrated to match five empirical moments: (i) an average entry rate (f_E) of 0.13, as in the BDS data (Figure 1, Panel B); (ii) a research wage premium ($w^r/w^p - 1$) of 12%, as observed in the BLS data (Figure

[22] Specifically, the two parameters are solved from $1/\xi = 0.17$, $1/q\xi = 0.3$ and $\overline{\xi} = \xi q$.

2, Panel D); (iii) a research employment share (n/L) of 5.5%, consistent with BLS data (Figure 2, Panel B); (iv) an incumbent's share of research employment of 48%, as documented in Akcigit and Goldschlag (2023); and (v) a technological growth rate of 1.3% (Figure 1, Panel A). Table 10 shows that our calibrated model successfully replicates these observed moments.

7 Quantitative results

In this section, we first quantify the impact of the declining elasticity of labor supply for researchers on wages, employment, innovation probability, and research employment share. We then examine the increasing difficulty of finding ideas and its effects on innovation and creative destruction, showing how this phenomenon amplifies strategic hiring in the model. Finally, we study R&D subsidies for both incumbent firms and new entrants and assess the role of dynamic attraction.

The effect of a higher switching cost. We simulate a 10 percentage point decline in the short-run elasticity of research labor supply to match the observed drop from 0.17 in the pre-1995 period to 0.07 post-1995, as estimated in Section 4. We implement this decline by increasing the switching cost $\overline{\xi}$ from 3.33 to 8.09. This adjustment also implies a reduction in the long-run elasticity from 0.3 to 0.12, which is consistent with the estimate provided in Section 4.

Table 11: Reduction in the elasticity of researchers' labor supply of 10 percentage points

	(1)	(2)	(3)
	Benchmark	High $\overline{\xi}$	% change
(1) Short-run elasticity of research labor supply	0.17	0.07	-58.8%
(2) Long-run elasticity of research labor supply	0.3	0.12	-58.8%
(3) Incumbent's share of researchers	48%	54.8%	14.2%
(4) Research wage premium	12%	18.4%	53.4%
(5) Creative destruction probability	0.13	0.126	-3.17%
(6) Share of research employment	5.50%	5.73%	4.23%
(7) Technological growth rate	1.30%	1.27%	-2.54%

Table 11 presents the results. Column (1) reports steady-state values in the benchmark case, Column (2) reflects the high switching cost scenario, and Column (3) shows percentage changes. Lower elasticity strengthens defensive hiring, leading incumbents to employ more researchers and raise wages. The incumbent's share of researchers rises from 48% to 54.8%, while the research wage premium increases from 12% to 18.4%.

Higher research wages have two opposing effects on technological growth. First, as shown in the fifth row, they reduce firm entry, lowering the creative destruction probability from 0.13 to 0.126, which slows growth. Second, as shown in the sixth row, they encourage more workers to enter research occupations, increasing the research employment share from 5.5% to 5.73%. However, since these additional researchers are absorbed by incumbents with low R&D intensity, the positive effect is weak and outweighed by the decline in creative destruction. As a result, the technological growth rate falls from 1.3% to 1.27% in the high-switching-cost case.

The incumbent's strategic behavior when ideas are getting harder to find. Next, we examine how increasing the difficulty of finding new ideas affects the strategic behavior of incumbents. We capture this by raising the shape parameter of the Pareto distribution for entrants' R&D efficiency, λ, from 1.48 to 1.63 (a 10% increase). A higher λ skews the distribution leftward, increasing the proportion of low-efficiency potential entrants while limiting the number of highly efficient entrants on average.

Table 12: The effect of a more left-skewed entrant R&D efficiency

	(1)	(2)	(3)	(4)
	Benchmark	High λ	High λ and high $\bar{\xi}$	% change
(1) Shape parameter	1.48	1.63	1.63	0
(2) Short-run elasticity	0.17	0.17	0.07	-58.8%
(3) Long-run elasticity	0.3	0.3	0.12	-58.8%
(4) Incumbent's share of researchers	48%	36.5%	44.8%	22.93%
(5) Research wage premium	12%	19%	25.3%	33.62%
(6) Creative destruction probability	0.13	0.094	0.091	-3.86%
(7) Share of research employment	5.50%	5.75%	5.98%	4.03%
(8) Technological growth rate	1.30%	0.96%	0.93%	-3.02%

Column (2) of Table 12 reports the steady-state values of selected variables when λ is increased, while the switching cost ξ remains at its benchmark value. For comparison, Column (1) presents results for the benchmark calibration, identical to Column (1) of Table 11.

A higher λ directly reduces the probability of creative destruction from 0.13 to 0.094 (sixth row, Table 12), leading to a decline in technological growth from 1.3% to 0.96% (eighth row, Table 12).

However, a higher λ also increases the density of potential entrants at the threshold, $\Psi'(\underline{k})$, since $\underline{k}$ lies in the lower part of the R&D efficiency distribution. This amplifies the impact of research wages on firm entry, prompting incumbents to raise wages strategically. As shown in the fifth row of Table 12, the research wage premium rises from 12% to 19%, indicating stronger defensive hiring when ideas become harder to find. Consequently, more workers opt for research occupations, increasing the share of research employment from 5.5% to 5.75%.

Finally, as shown in the fourth row of Table 12, the incumbent's share of researchers declines from 48% to 36.5% despite intensified defensive hiring, evidenced by the rising research wage premium. This seemingly counterintuitive result stems from a general equilibrium effect: lower creative destruction increases the incumbent's value, making innovation more attractive to potential entrants. Consequently, more entrants -albeit less efficient- enter the market and hire researchers despite higher wages. In summary, our analysis indicates that incumbents raise wages more aggressively when potential entrants face lower innovation probabilities.

Column (3) of Table 12 shows the results when both ξ and λ are set to high values, while Column (4) presents the percentage changes from Column (3) to Column (4) due to the increase in ξ, conditional on a high λ.

The reduced elasticity of research labor supply strengthens defensive hiring incentives, prompting incumbents to hire more researchers and raise their wages. As in Table 11, higher switching costs in the high λ environment lead to a reduction in research labor supply elasticity, an increase in the incumbent's share of researchers and wage premium, a decline in the probability of creative destruction, an increase in the share of research employment, and a drop in technological growth.

However, comparing the final columns of Tables 11 and 12, we observe that the impact of higher switching costs on the incumbent's share of researchers, the probability of creative destruction, and technological growth is stronger in the high λ environment than in the benchmark case, even with a milder increase in the wage premium. Intuitively, a high λ means more potential entrants are near the entry threshold, making research wages more influential on entry. Consequently, the incumbent's strategic behavior leads to a sharper decline in entry and technological growth, further increasing its share of researchers.

In conclusion, our analysis reveals that the strategic behavior of incumbent firms has a more pronounced impact on firm entry and technological growth when potential entrants face lower innovation probabilities.

R&D subsidies. In this subsection, we examine the impact of government-funded R&D subsidies for both incumbent firms and new entrants at rates τ_I and τ_E, respectively. These subsidies are financed through lump-sum taxes.

The free-entry condition for new entrants is now:

$$\underline{k}_{j,t} V_{E,j,t} - (1-\tau_E) w^r_{j,t} = 0,$$

and the first-order condition for incumbents is:

$$(1-\tau_I) w^r_{j,t} = \overbrace{\phi \Delta \pi_t}^{\text{mpr}} - \frac{\overbrace{(1-\tau_I) n_{j,I,t}}^{\text{monopsony}} - \overbrace{\underline{k}_{j,t} \Psi' \underline{k}'_{j,t} \widehat{V}_t}^{\text{Defensive hiring}} + \overbrace{\Phi_{j,t} \left[(1-\tau_I) w^r_{j,t+1} - \phi \Delta \pi_{j,t+1} \right]}^{\text{Dynamic attraction}}}{\Psi' \underline{k}'_{j,t} + \partial L_{j,t} / \partial w^r_{j,t}}.$$

Our first exercise subsidizes new entrants at a rate of $\tau_E = 0.1$, while keeping the incumbent subsidy rate at $\tau_I = 0$. The results appear in the second column of Table 13. The second exercise subsidizes incumbents at a rate of $\tau_I = 0.098$, matching the total subsidy in the first exercise, while setting the new entrant subsidy rate to $\tau_E = 0$. The results appear in the third column of Table 13. For reference, the benchmark case with no subsidies is shown in the first column of Table 13.

Table 13: R&D subsidies

	(1)	(2)	(3)
	Benchmark	Subs. entrants	Subs. incumbents
(1) τ_E	0	0.1	0
(2) τ_I	0	0	0.098
(2) Incumbent's share of researchers	48%	42.1%	53.7%
(3) Research wage premium	12%	12.2%	18.6%
(4) Creative destruction probability	0.13	0.135	0.127
(5) Share of research employment	5.50%	5.51%	5.74%
(6) Technological growth rate	1.30%	1.34%	1.28%

As expected, subsidizing entrants reduces the incumbent's share of researchers and increases creative destruction. In contrast, subsidizing incumbents raises their share of researchers and lowers creative destruction. Since incumbents have low R&D efficiency in our calibration, subsidizing entrants fosters technological growth, while subsidizing incumbents hinders it.

Subsidizing incumbents raises the wage premium by increasing the demand for researchers (a conventional pass-through effect of the subsidy) and reducing classic monopsony concerns, prompting incumbents to offer higher research wages. Thus, the share of research employment rises. Conversely, subsidizing new entrants has little effect on the research wage premium or the share of research employment.

In other words, to foster technological growth and correct market distortions, the government should subsidize new entrants and tax incumbent firms. These taxes counteract defensive hiring and reduce overall distortion, even at the cost of amplifying the monopsony effect. In contrast, traditional models, where monopsony or similar market power is the primary distortion, recommend subsidizing incumbents to mitigate monopsony. For example, Edmond et al. (2023) propose subsidizing large firms, with the optimal rate proportional to firm size, as larger firms tend to have higher markups.

The role of dynamic attraction. To assess the role of dynamic attraction, we shut down long-run switching by setting $q = 1$. To maintain short-run elasticity at its original level of 0.17, we adjust $\overline{\xi}$ to $1/0.17$, resulting in a long-run elasticity of 0.17.

Table 14: Forbidding long-run switching

	(1)	(2)	(3)
	Benchmark	Short-run switching only	% change
(1) Short-run elasticity	0.17	0.17	0
(1) Long-run elasticity	0.3	0.17	-43.3%
(2) Incumbent's share of researchers	48%	52.4%	9.22%
(3) Research wage premium	12%	16.1%	34.03%
(4) Creative destruction probability	0.13	0.127	-2.01%
(5) Share of research employment	5.50%	5.66%	2.7%
(6) Technological growth rate	1.30%	1.28%	-1.61%

Table 14 presents the results. Column (1) reports the steady-state values in the benchmark scenario, where researchers switch at various horizons. Column (2) displays the outcomes when researchers can only switch sectors in the current period. Column (3) shows the percentage changes. Switching at short-run only turns off the dynamic attraction consideration, leading incumbents to employ more researchers and increase wages. The incumbent's share of researchers increases from 48% to 52.4%, while the research wage premium increases from 12% to 16.1%. Consequently, the creative destruction probability decreases from 0.13 to 0.127, decelerating the technological growth rate from 1.3% to 1.28%. Finally, the higher research wage premium results in an increase in the share of research employment from 5.5% to 5.66%.

8 Conclusion

Our analysis highlights the interplay between monopsony power in the labor market for researchers and the inelastic supply of researchers as a key driver of the persistent decline in creative destruction and productivity growth, despite rising R&D spending and researcher employment in the US over the past two decades.

Our theory explains these trends through defensive hiring by incumbent firms, which internalize the effect of hiring researchers on competitors' innovation probabilities. In monopsonistic markets with an inelastic supply of researchers, incumbents overhire to deter entrant innovation and preserve market dominance. Ideas getting harder to find amplifies this mechanism.

Empirical evidence supports this theory, showing that the elasticity of research labor supply is low and has declined since the mid-1990s. Moreover, incumbent R&D spending is negatively correlated with creative destruction and sectoral TFP growth while extending incumbents' lifespans, effects that are stronger in industries with inelastic researcher supply, consistent with our model's predictions.

Our quantitative model shows that higher switching costs for researchers further reduce labor supply elasticity, slow creative destruction and technological growth, and increase both researcher employment and wage premiums. Lower R&D efficiency among potential entrants magnifies these effects, reinforcing the "ideas are getting harder to find" phenomenon we pointed out above.

These findings highlight promising directions for future research. One possibility is that inelastic researcher supply results from increasing knowledge specialization. Measuring specialization, tracking its evolution across fields, and studying its implications for technological growth in a monopsonistic labor market would be valuable. Another avenue is optimizing education systems and policies. Could interdisciplinary education, fostering knowledge transfer and researcher mobility, mitigate incumbents' strategic hiring? More broadly, could online education, remote work, or alternative knowledge-sharing counteract the negative effects on TFP and creative destruction? These questions merit further exploration.

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Online Appendix

A Additional figures and tables

Table A.1: Incumbent R&D expenditure and firm entry: panel estimation

Panel A: One-year Ahead				
	(1)	(2)	(3)	(4)
Dependent variable	Entry rate (t+1), BDS		Listing rate (t+1), Compustat	
$R\&D_{j,t}$	-0.67***	-1.57***	-0.57***	-1.11***
	(0.08)	(0.16)	(0.15)	(0.29)
$R\&D_{j,t} \times \eta_j$		1.71***		0.98***
		(0.27)		(0.45)
Industry FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Adj R-squared	0.73	0.73	0.37	0.37
Observations	1,608	1,605	2,012	2,009
Panel B: Three-years Ahead				
	(1)	(2)	(3)	(4)
Dependent variable	Entry rate (t+3), BDS		Listing rate (t+3), Compustat	
$R\&D_{j,t}$	-0.73***	-1.66***	-0.61***	-1.18***
	(0.08)	(0.15)	(0.10)	(0.14)
$R\&D_{j,t} \times \eta_j$		1.80***		1.05***
		(0.25)		(0.28)
Industry FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Adj R-squared	0.78	0.79	0.52	0.52
Observations	1,466	1,466	1,845	1,845

The data span 1970-2019 on a yearly basis. The dependent variable is the average entry rate over the subsequent five years. The independent variable, $R\&D$, represents the average R&D expenditure of incumbent firms. η denotes the elasticity of research labor supply.

Table A.2: Incumbent R&D expenditure and sectoral productivity: panel estimates

Panel A: One-year Ahead				
	(1)	(2)	(3)	(4)
Dependent variable	$\Delta z_{-i,j,t+1}$		$\Delta z_{j,t+1}$	
$R\&D_{i,j,t}$	-0.033	-0.101		
	(0.092)	(0.18)		
$R\&D_{i,j,t} \times \eta_j$		0.096		
		(0.37)		
$R\&D_{j,t}$			-0.006	-0.009
			(0.004)	(0.009)
$R\&D_{j,t} \times \eta_j$				0.004
				(0.01)
Industry FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Adj R-squared	0.16	0.16	0.32	0.32
Observations	68,867	68,784	687	687
Panel B: Three-years Ahead				
	(1)	(2)	(3)	(4)
Dependent variable	$\Delta z_{-i,j,t+3}$		$\Delta z_{j,t+3}$	
$R\&D_{i,j,t}$	-0.054	-0.21**		
	(0.044)	(0.100)		
$R\&D_{i,j,t} \times \eta_j$		0.221*		
		(0.127)		
$R\&D_{j,t}$			-0.009**	-0.018**
			(0.003)	(0.008)
$R\&D_{j,t} \times \eta_j$				0.014
				(0.011)
Industry FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Adj R-squared	0.10	0.10	0.46	0.46
Observations	51,877	51,826	678	678

The data span 1970-2019 on a yearly basis. The dependent variable is the productivity growth rate (percentage points). The independent variable, $R\&D$, represents R&D expenditure. η denotes the elasticity of research labor supply.

Table A.3: Incumbent R&D expenditure and firm entry: panel estimation, long-run elasticity

	(1)	(2)	(3)	(4)
Dependent variable	Entry rate (t+5), BDS		Listing rate (t+5), Compustat	
$R\&D_{j,t}$	-0.76***	0.14	-0.66***	-0.40
	(0.07)	(0.25)	(0.08)	(0.25)
$R\&D_{j,t} \times \eta_j^l$		-1.00***		-0.28
		(0.27)		(0.25)
Industry FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Adj R-squared	0.82	0.82	0.61	0.61
Observations	1,339	1,339	1,696	1,696

The data span 1970-2019 on a yearly basis. The dependent variable is the average rate of entry in the subsequent five years. The independent variable, $R\&D$, is the average R&D expenditure across incumbent firms. η^l is the elasticity of research labor supply.

Table A.4: Incumbent R&D expenditure and sectoral productivity: panel estimation, long-run elasticity

	(1)	(2)	(3)	(4)
Dependent variable	$\Delta z_{-i,j,t+5}$		$\Delta z_{j,t+5}$	
$R\&D_{i,j,t}$	-0.09*	0.03		
	(0.14)	(0.10)		
$R\&D_{i,j,t} \times \eta_j^l$		-0.14		
		(0.16)		
$R\&D_{j,t}$			-0.01*	0.01
			(0.004)	(0.01)
$R\&D_{j,t} \times \eta_j^l$				-0.02*
				(0.01)
Industry FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Adj R-squared	0.14	0.14	0.56	0.55
Observations	39,299	39,271	589	589

The data span 1970-2019 on a yearly basis. The dependent variable is the productivity growth rate (percentage points). The independent variable, $R\&D$, represents R&D expenditure. η^l denotes the long-run elasticity of research labor supply.

Table A.5: Incumbent R&D expenditure and lifespan of the incumbent firm: cross-sectional estimation, long-run elasticity

	(1)	(2)
Dependent variable	Lifespan	
$R\&D_{i,j}$	0.67***	0.43***
	(0.04)	(0.13)
$R\&D_{i,j} \times \eta^l_j$		0.28**
		(0.14)
Industry FE	Yes	Yes
Cohort FE	Yes	Yes
Adj R-squared	0.41	0.41
Observations	7,429	7,392

The data span 1970-2019 on a yearly basis. The dependent variable is the lifespan of incumbent firms. The independent variable, $R\&D$, is the logarithm of average R&D expenditure. η^l denotes the long-run elasticity of research labor supply.

B The model-implied wage and value of innovation

Here, we show that researchers' wages are proportional to the value of innovation, a key assumption in our empirical analysis.

When an incumbent's R&D succeeds, its value becomes:

$$V^*_{j,I,t} = \left(1 - \frac{1}{\gamma\chi}\right) Y_{j,t} + \frac{V_{j,I,t+1}}{1+r_t},$$

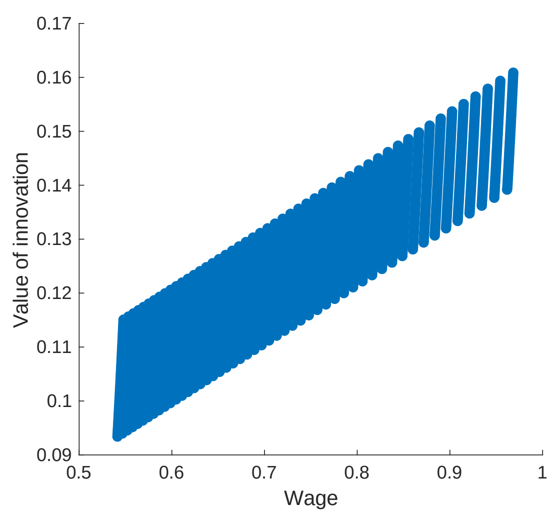
which exceeds $V_{j,I,t}$ (the incumbent's expected value before innovation) for two reasons. First, the successful incumbent secures higher profits with certainty. Second, it guarantees survival into the next period.

The value of innovation is:

$$\Delta V_{j,I,t} = V^*_{j,I,t} - V_{j,I,t},$$

which, under efficient financial markets, corresponds to the increase in the incumbent's market capitalization following the announcement of successful innovation.

Figure B.1: Wage is proportional to the market value of innovation



To demonstrate that the wage $w^r_{j,t}$ is proportional to the market value of innovation $\Delta V_{j,I,t}$, we introduce shocks to γ and r_t, allowing the size of innovation and the risk premium to vary across innovations and incumbent firms. Figure B.1 shows a strong positive relationship between $w^r_{j,t}$ and $\Delta V_{j,I,t}$.

C The derivation of the sectoral research labor supply curve

We assume that the incumbent of sector j deviates from the homogeneous wage in period t. To derive the multi-horizon labor supply curve, we must specify the full trajectory of the wage change. We assume the deviation persists until period $t+1$, following $w^r_{j,t+1} - w^r_{t+1} = \rho_w(1+r_t)(w^r_{j,t} - w^r_t)$, with $\rho_w \geq 0$. After that, the deviation reverts to zero, i.e., $w^r_{j,t+k} = w^r_{t+k}$ for $k > 1$. This simplification is useful, as we only consider immediate and one-period-delayed job switching. However, our derivation can accommodate more persistent wage changes without altering the results.

The sectoral labor supply curve for researchers consists of two segments. In the first, the wage in sector j exceeds that of other sectors, attracting workers from elsewhere. In the second, the wage in sector j is lower, prompting workers to leave for other sectors. We formally define these two segments below.

Segment 1: $w^r_{j,t} > w^r_t$. Since sector j offers a higher wage, researchers in the other $J-1$ sectors are incentivized to move to sector j. The total measure of potential job switchers is $m_t = n^r_t(J-1)$. Researchers with switching costs $\xi_{i,t}$ lower than the sum of discounted wage differentials $q(w^r_{j,t} - w^r_t) + (1-q)(w^r_{j,t+1} - w^r_{t+1})/(1+r_t) = [q + \rho_w(1-q)](w^r_{j,t} - w^r_t)$. Thus, the measure of actual job switchers is:

$$\widehat{m}_t = \left(\frac{w^r_{j,t}/w^r_t - 1}{\bar{\xi}/[q + \rho_W(1-q)]} \right) n^r_t, \tag{A-1}$$

Therefore, the measure of actual short-run (immediate) and long-run (delayed) job switchers is:

$$\widehat{m}^s_t = q\widehat{m}_t = q[q + \rho_W(1-q)] \left(\frac{w^r_{j,t}/w^r_t - 1}{\bar{\xi}} \right) n^r_t,$$

and

$$\widehat{m}^l_t = (1-q)\widehat{m}_t = (1-q)[q + \rho_W(1-q)] \left(\frac{w^r_{j,t}/w^r_t - 1}{\bar{\xi}} \right) n^r_t,$$

respectively.

Define $\xi = q^{-1}\bar{\xi}/[q + \rho_W(1-q)]$, the above equations become:

$$\widehat{m}^s_t = \left(\frac{w^r_{j,t}/w^r_t - 1}{\xi} \right) n^r_t, \tag{A-2}$$

and

$$\widehat{m}_t^l = \frac{(1-q)}{q}\left(\frac{w_{j,t}^r/w_t^r - 1}{\xi}\right) n_t^r, \tag{A-3}$$

respectively.

Segment 2: $w_{j,t}^r < w_t^r$. Since sector j offers a lower wage, researchers in sector j are incentivized to move to the other $J-1$ sectors. The total measure of potential job switchers is $m_t = n_t^r$. Researchers with switching costs lower than $q(w_{j,t}^r - w_t^r) + (1-q)(w_{j,t+1}^r - w_{t+1}^r)/(1+r_t)$ will transition to other sectors. The measure of researchers moving from sector j is:

$$\widehat{m}_t = \left(\frac{1 - w_{j,t}^r/w_t^r}{\bar{\xi}/[q + \rho_W(1-q)]}\right) n_t^r.$$

Therefore, the measure of actual short-run and long-run job switchers is:

$$\widehat{m}_t^s = q\widehat{m}_t = \left(\frac{1 - w_{j,t}^r/w_t^r}{\xi}\right) n_t^r,$$

and

$$\widehat{m}_t^l = (1-q)\widehat{m}_t = \frac{(1-q)}{q}\left(\frac{1 - w_{j,t}^r/w_t^r}{\xi}\right) n_t^r,$$

respectively.

The above equations imply that the labor supply for researchers in sector j is:

$$L_{j,t+1} = n_{t+1}^r + \frac{1}{\xi}\left(\frac{w_{j,t+1}^r - w_{t+1}^r}{w_{t+1}^r}\right) n_{t+1}^r + \frac{(1-q)}{q\xi}\left(\frac{w_{j,t}^r - w_t^r}{w_t^r}\right) n_t^r,$$

or, equivalently,

$$\frac{L_{j,t+1} - n_{t+1}^r}{n_{t+1}^r} = \frac{1}{\xi}\left(\frac{w_{j,t+1}^r - w_{t+1}^r}{w_{t+1}^r}\right) + \frac{(1-q)}{q\xi}\frac{n_t^r}{n_{t+1}^r}\left(\frac{w_{j,t}^r - w_t^r}{w_t^r}\right), \tag{A-4}$$

which includes the immediate (short-run) switchers in period $t+1$ and delayed (long-run) switchers whose decisions were made in period t.

Elasticities of research labor supply The short-run elasticity is $1/\xi$, which quantifies the percentage increase in the number of job switchers in period t in response to wage deviations in period t.

Aligned with our empirical specification, the long-run elasticity captures the comovement between the increase in job switchers in period $t+1$ and wage deviations in period $t+1$ due to initial wage deviations in period t. It is useful to rewrite equation (A-4) as:

$$\frac{L_{j,t+1} - n^r_{t+1}}{n^r_{t+1}} = \left[\frac{1}{\xi} + \frac{(1-q)}{\xi q \rho_w (1+r_t)} \frac{n^r_t}{n^r_{t+1}}\right] \left(\frac{w^r_{j,t+1} - w^r_{t+1}}{w^r_{t+1}}\right),$$

which implies that the long-run elasticity is $\frac{1}{\xi} + \frac{(1-q)}{\xi q \rho_w (1+r_t)} \frac{n^r_t}{n^r_{t+1}}$.

Since the empirical counterpart of research wages is stock prices, it is reasonable to assume that $E_t(w^r_{j,t+1}) = w_{j,t}$, implying $\rho_w(1+r_t) = 1$. We also have $n^r_t = n^r_{t+1}$ on the BGP. Therefore, the long-run elasticity of research labor supply simplifies to $1/\xi + (1-q)/(\xi q) = 1/(q\xi)$. Moreover, this implies that $\xi = \overline{\xi}\left(\frac{1/q+r}{1+r_t}\right) \approx \overline{\xi}/q$.

D Summary of the quantitative model

Table D.6: Summary of the quantitative model

Incumbent's F.O.C.	$w^r = \phi\Delta\pi - \frac{n_I - \underline{k}\Psi'\underline{k}'\widehat{V}}{\Psi'\underline{k}' + \frac{1}{\xi}\frac{n^r}{w^r}[1+(\frac{1-f_E}{1+r})(\frac{1-q}{q})]}$
Entrant's free-entry condition	$\underline{k}V_E - w^r = 0$
Incumbent's value	$V_I = \phi n_I \left(1 - \frac{1}{\gamma\chi}\right) Y + (1 - \phi n_I - f_E)\left(1 - \frac{1}{\chi}\right) Y$ $- n_I w^r + (1 - f_E)(1+g)\frac{V_I}{1+r}$
Entrant's value	$V_E = \left(1 - \frac{1}{\gamma\chi} - \iota\right) Y + (1+g)\frac{V_I}{1+r}$
Aggregate measure of researchers	$\frac{N^r}{L} = \frac{1}{b_2}\left(\frac{w^r - w^p}{w^p}\right) - \frac{b_1}{b_2}$
Sectoral research labor market clearance	$N^r = J \cdot [n_I + \Psi(\underline{k})]$
Output	$Y = \frac{\gamma(L - N^r)}{(f_I + f_E)\gamma + (1 - f_I - f_E)}$
Interest rate	$r = -ln(\beta) + g$
Growth rate	$g = (\gamma - 1)\left[1 - (1 - f_I - f_E)^J\right]$