Inelastic Supply of Innovators, Monopsony Power, and Creative Destruction*

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Abstract

In this paper, we link the contrasting evidence on the persistent decline in creative destruction, the fall in productivity growth occurring together the simultaneous increase in R&D spending and the knowledge specialization with the forces of monopsony power and the strategic hiring of researchers by incumbent firms. We develop an equilibrium model of creative destruction under monopsony power that shows that incumbent firms undertake the strategic hiring of researchers to deter innovation from entrant firms and preserve market dominance. Low elasticity of the labor supply of innovators heightens strategic hiring. We assemble a novel dataset that matches the universe of patent applications in the US with the stock market returns from inventions, and we establish that the elasticity of labor supply of R&D workers is low and it has steadily declined since the mid-1990s. We show that spending in R&D by incumbent firms is negatively related to creative destruction and sectoral TFP growth while increasing the life expectancy of incumbent firms, and these dynamics are stronger in industries with more inelastic supply of R&D workers. An extended version of our model outlines the quantitative relevance of our mechanism for productivity growth, creative destruction, and economic policy.

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

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1 Introduction

Productivity growth and creative destruction —the termination of firms by the entrance of more competitive firms— have fallen substantially in the US over the past twenty years. Yet, the spending on R&D activities and the hiring of specialized workers have increased considerably over the same period.[1] Big corporations devote increasingly large resources to employ and generously retribute highly-skilled workers. Yet, these forces fail to foster innovation and productivity growth in the economy. Are these seemingly conflicting trends an equilibrium outcome of market incentives? What forces may account for those diverse trends? And what are the implications of those forces for the pace of innovation, growth of productivity, and the role of economic policy?

Our study provides a novel theory that accounts for the seemingly contrasting evidence by considering the *interplay* between the strategic behavior of incumbent firms in monopsonistic markets and the elasticity of the labor supply of researchers. We first develop a simple model of monopsonistic competition and strategic behavior of dominant firms that shows that high wages and employment for research workers is the optimal choice by incumbent firms to deter innovation from entrant firms and preserve market dominance. Our theory shows that this mechanism is powerful when the labor supply of researchers is relatively inelastic. We test our mechanism and the resulting predictions of our theory assembling a novel dataset that matches the universe of patent applications in the US with the stock market returns from inventions across 281 four-digit Naics industries. We establish several new results showing the persistent decline in the elasticity of the labor supply of research workers across time and industries, and evincing the negative link between R&D expenditures by market leaders with sectoral productivity growth and creative destruction. Finally, we develop a full, quantitative model to assess the quantitative implications of our theory and run counterfactual policy analysis.

Theoretical framework. We develop a simple model of creative destruction in monopsony markets for research workers based on the Aghion-Howitt model of Shumpeterian destruction

[1]Section 2 provides evidence on these empirical regularities.

(Aghion and Howitt, 1992). To fix ideas, we begin by studying the standard monopsony market, with the incumbent firm setting the market wage while accounting for the effect of the wage on the labor supply. The incumbent strategically sets the wage below the marginal product of labor, decreasing employment and resulting in higher profits, which fosters the entrance of firms and creative destruction despite the lower share of income to research workers. We then show that these results are overturned if the incumbent firm accounts strategically for the effect of hiring research workers on the probability of entrant firms to innovate. In such a case, the incumbent firm optimally undertakes a "defensive-hiring" strategy by employing R&D workers to reduce the innovating probability of competitors, decreasing creative destruction. Thus, defensive hiring overturns the standard monopsony result of low employment, low wages, and high creative destruction.

Defensive hiring is the dominant strategy when: (i) the incumbent firm has low R&D productivity; (ii) the incumbent firm has strong decreasing returns to scale in R&D; and (iii) the expected profits of the entrant firms are low. Since the three conditions imply a reduction in the innovation probability for the incumbent and the entrant firms, defensive hiring becomes prevalent when "ideas are getting harder to find" (Bloom et al., 2020).

When defensive hiring is the dominant strategy, the elasticity of the labor supply of R&D workers is central to the strength of our mechanism in the economy. Defensive hiring is costly for the incumbent firm that strategically sets wages and employment at high levels to reduce the innovation probability of competitors, and our model shows that the effectiveness of such a strategy primarily hinges on the elasticity of the labor supply of R&D workers. Consider the case of a perfectly elastic labor supply of research workers. Hiring by the incumbent increases the wage due to the decreasing returns of the innovation process, which spurs an increase in the supply of R&D labor, requiring the incumbent firm to hire more aggressively to sustain defensive hiring to hinder the availability of research workers to potential competitors, further increasing wage costs. Hence, a highly elastic labor supply of researchers deters defensive hiring and preserves creative destruction. When the labor supply of research workers is inelastic, however, hiring by the incumbent firms curtails the availability of research workers to potential competitors without inducing an increase in wage costs. Hence, an inelastic labor supply of research workers encourages defensive hiring and impairs creative destruction. Thus, the strength of our mechanism relies on the testable assumption of a rigid labor supply for research workers, and the model provides several predictions on the link between R&D spending by incumbent firms with creative destruction and TFP growth in the economy. In particular, our model predicts:

- Incumbent firms' R&D negatively affects new firm entry.
- Incumbent firms' R&D positively affects their life expectancy.
- The above effects are stronger when the supply of research workers is inelastic.

Empirical results. We first validate the central mechanism of our theory by focusing on the elasticity of the labor supply of research workers, estimating the value, and studying the variations across time and industries; then, we assess the predictions of our theory by studying the effect of defensive hiring on TFP growth and creative destruction.

We assemble a novel dataset by combining 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 —the empirical counterpart for research workers in the model— to the market value of their patents elicited from the stock market prices —the empirical counterpart for the payoff for inventors in conducting research— we establish three new facts on the elasticity of the labor supply of research workers:

Fact 1. The labor supply of research workers is inelastic on average over the sample period. A 1% increase in the average market value of patents in a research field (adjusted for the number of co-inventors), which is our proxy for the expected payoff of inventors for undertaking research effort, attracts an additional 0.05% 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 0.07 between 1970 and 1995 to 0.02 between 1996 and 2019 (while the full sample point estimate is 0.05, as established in Fact 1). In other words, the labor supply of researchers has become increasingly inelastic over time.

Fact 3. The elasticity of labor supply of researchers is largely heterogeneous across fields. Since the exposure of industries to research fields is different, the elasticity of labor supply of researchers is strongly heterogeneous across industries.

We then study the implications of strategic hiring for creative destruction and TFP growth by combining 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. We establish the following new facts:

Fact 4. R&D spending by incumbent firms negatively predicts the creation of new firms in the same industry, and the relationship is stronger in industries with an inelastic labor supply of researchers.

Fact 5. R&D spending by incumbent firms negatively predicts the growth of TFP for firms in the same industry, and the pattern is stronger for industries with a low elasticity of research labor supply.

Fact 6. R&D spending by incumbent firms positively predicts the life expectancy of the incumbent firms, and the prediction is stronger for industries with a lower elasticity of research labor supply.

Quantitative model. Having validated empirically the central assumption on the inelastic labor suply of research workers, as well as the key theoretical predictions of our theory, we extend the simple model in a full, quantitative model to assess the quantitative implications of our theory and run counterfactual policy analysis. We calibrate the model to the U.S. data. Most importantly, the model calibrates a high switching cost for research workers, which entails a low elasticity of research labor supply, a target moment obtained from Fact 1. Our quantitative model establishes four important results.

First, defensive hiring prevails as the dominating driving force due to the low elasticity of research labor supply. As a result, incumbent firms strategically set higher wages and recruit research workers aggressively, leading to low creative destruction and business dynamism. This hurts technological growth due to the lower R&D productivity of incumbents than the entrants, calibrated to the finding of Akcigit and Goldschlag (2023).

Second, the higher wage set by incumbent firms attracts more workers to choose research careers, which is a general equilibrium effect that benefits technological growth, similar to a subsidy to research occupation. However, this benefit is dominated by the proceeding detrimental effect of defensive hiring on creative destruction.

Third, conditional on the elasticity of research labor supply, the motive of defensive hiring is stronger when the R&D productivity is lower. In other words, the incumbent firms would repress creative destruction more aggressively when "ideas are getting harder to find" (Bloom et al., 2020).

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

Related research. Our analysis relates to research that studies the effect of the strategic behavior of incumbent firms in conducting R&D on technological growth. Argente et al. (2020) and Akcigit and Goldschlag (2023) show that R&D spending by large firms fails to spur sustained innovation while deterring market competition. Bloom et al. (2020) and Bilal et al. (2021) that the slowing process of finding ideas hinders growth and creative destruction. Cunningham et al. (2021), Bao and Eeckhout (2023), and Benkert et al. (2023) show that incumbent firms strategically deploy R&D spending and use acquisition to enhance their own market power. We show that the defensive hiring of research workers is an effective strategy to retain the market power by incumbent firms in monopsony markets with low elasticity of labor supply to explain important patterns in TFP and creative destruction in US data.

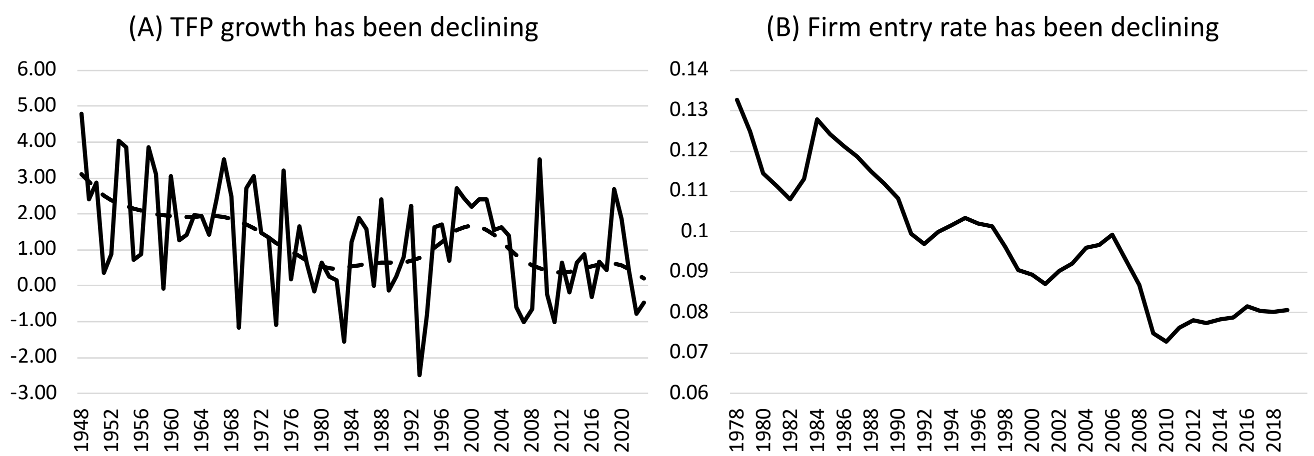
We also relate to the literature on monopsony power. A bulk of research (Azar et al., 2019; Berger et al., 2022; Manning, 2021) focuses on the classic monopsony market with dominant firms setting a lower-than-competitive wage while sub-hiring workers. Our paper is mostly related to Parente and Prescott (1999) and Fernández-Villaverde et al. (2021), who show that dominant firms increase hiring to strengthen the monopsony power in the product and labor markets, opposite to the prediction of the classic monopsony model. Different from the previous literature that primarily studies the decreasing labor share and increasing labor and product market concentration, we study the implication of monopsony power in researchers' labor market for technological growth.

Structure of the paper. The remainder of the paper is organized as follows. Section 2 provides motivating evidence. Section 3 develops a simple model of creative destruction in monopsony markets for research workers that provides our key results and the testable predictions of our theory. Section 4 assembles a new dataset that provides novel evidence on the inelastic supply of innovators and the negative effect of R&D spending on creative destruction and productivity growth. Section 5 develops an extended version of our simple model to study quantitive implications and policy analysis.

2 Motivating evidence

In this section, we provide a unified picture of the disparate developments in TFP, R&D spending, firm entrance, and the number, specialization and compensation of researchers in the US economy in the period 1929-2020. Our key message is the persistent decline in the growth rates of TFP and creative destruction concomitant to the steady increase in the number, remuneration, and specialization of R&D workers over the same period.

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



In Panel (A), the solid curve displays the utilization-adjusted TFP growth rate constructed by Fernald (2014). The dashed curve is the trend estimated with an HP filter. Panel (B) displays the firm entry rate measured as the ratio of the number of new firms to the total number of firms in the BDS data.

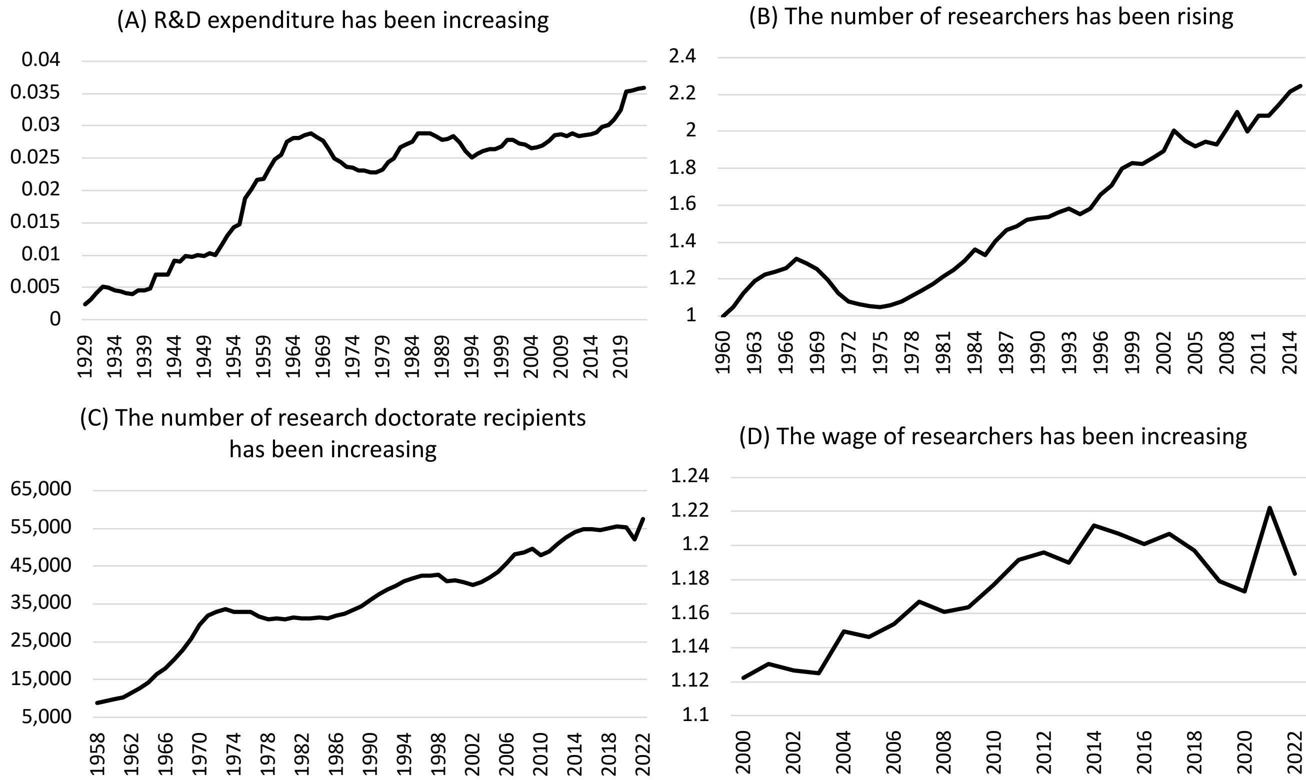
Panel (A) in Figure 1 shows the annual utilization-adjusted TFP growth (black line), constructed using the methodology in Fernald (2014), and the trend of the series from the HP-filer (dashed line) for the period 1948-2023. The figure shows the gradual fall in the trend of TFP growth over the sample period, corroborating the analogous findings in several studies (Gordon, 2012, Akcigit and Ates, 2021, and Acemoglu et al., 2023).

Panel (B) in Figure 1 shows the entry rate for firms in the period 1978-2018. We measure the entry rate by the ratio between the number of new firms and the number of firms recorded in the Business Dynamics Statistics (BDS) dataset, administered by the US Census Bureau. The figure shows a steady decline in the rate of firms' entry over the period that is consistent with the results of several studies (Decker et al., 2020 and Akcigit and Ates, 2023)

Panel (A) in Figure 2 shows the share of R&D expenditure as a fraction of total GDP for the period 1929-2020. R&D expenditure is from the Bureau of Economic Analysis (BEA) administered by the US Department of Commerce. The figure shows that the increase in R&D spending is mostly uninterrupted throughout the past 100 years of US history.

Panel (B) in Figure 2 shows the ratio of the effective number of researchers to working-age population constructed by Bloom et al. (2020) for the period 1960-2015. The series shows an

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



Panel (A) shows the share of R&D investment in US GDP. Panel (B) shows the ratio of the effective number of researchers constructed by Bloom et al. (2020) to working-age population. 1950 is normalized to one. Panel (C) shows the number of research doctorate recipients from U.S. colleges and universities constructed by NSF. Panel (D) shows the ratio of the median annual wage of research occupations to the median annual wage for undergraduate degree and higher. Research occupations include Computer and Mathematical Occupations (occupation code 15-0000) and Life, Physical, and Social Science (occupation code 19-0000). Data is from BLS.

upward trend that is consistent with the increase in R&D spending in the economy.

Panel (C) in Figure 2 shows the number of recipients of research doctorate for the period 1958-2022, constructed using data from the National Science Foundation (NSF). The series shows a steep increase in the inflow of doctorate researchers evincing a twelvefold increase from the start of records in 1958. The upward trend is consistent with, and partially accounts for, the sharp increase in the number of researchers shown in Panel (B).

Panel (D) in Figure 2 shows the ratio of the median-annual wage of research occupations to the median-annual wage for an undergraduate degree or higher from the Bureau of Labor Statistics (BLS) for the period 2000-2022. The figure shows that researchers have a higher wage growth compared to workers with an undergraduate degree or higher.

To summarize, our collection of evidence shows that the rates of TFP growth and entry of new firms in the economy have declined significantly despite the substantial increase in aggregate R&D spending, the rise in the number, remuneration, and knowledge specialization of researchers. In the next section, we develop a theory that unifies these seemingly contrasting empirical regularities.

3 A simple model of creative destruction and monopsony

We develop a simple model of creative destruction in a monopsony market for research workers that accounts for the facts presented in Section 2. The central mechanism in the model hinges on the interplay between "defensive-hiring" arising from the forces of the monopsony market and the inelastic supply of R&D workers. Our simple model relies on the assumption of an inelastic labor supply of research workers and provides several predictions on creative destruction and TFP growth that we will test in the data (Section 4). We will extend our simple framework to a comprehensive dynamic model to study quantitative implications and economic policy (Section 5).

3.1 Economic environment

The model is static, based on the parsimonious framework by Aghion and Howitt (2005), enriched with a sectoral labor market for research workers and strategic behavior in hiring from the incumbent firm. The economy comprises J sectors, each populated by an incumbent firm holding monopoly power and producing one unit of non-storable goods at a unitary marginal cost. The sectors are symmetric, so we drop the sectoral index. The monopolistic incumbent firm faces competition from an infinite number of entrants that produce a unit of the same goods at the marginal cost $\chi > 1$, which the incumbent uses as the price, yielding profits equal to $\pi = \chi - 1$. The incumbent firm and the new entrants hire research workers to innovate production. If innovation is successful, the innovating firm (either incumbent or entrant) improves the quality of output by $\gamma > 1$. If the entrant innovates successfully, it drives the incumbent firm out of business becoming the new market leader.

Innovation probability for the incumbent firm. We assume that the incumbent firm has an innovation probability equal to:

$$f_I = \phi n_I^{\alpha} / \alpha,$$

where n_I is the measure of research workers hired by the incumbent firm, and $\phi > 0$ is the R&D productivity of the incumbent firm. The probability of innovating holds decreasing returns to scale in the R&D process, represented by the parameter $\alpha < 1$, consistent with the empirical evidence in Klette and Kortum (2004).[2] If the incumbent firm successfully innovates, operating profits increase proportionally to the size of the innovation, thus raising profits to $\gamma\pi$.

Innovation probability for entrant firms. In each sector, there is a continuum of potential entrants, indexed by $k \in [0, 1]$, where k also tracks the level of idiosyncratic R&D productivity of each entrant. Without loss of generality, we assume that upon entry, each entrant k hires a unitary measure of research workers at the equilibrium wage. If innovation is successful, creative destruction takes place and the innovating entrant gains operating profits $\gamma\pi$, while the incumbent firm and the remaining entrants earn zero profits and exit the market. Each entrant has a different capacity to innovate that is proportional to the idiosyncratic productivity and equal to ψk, where k is the level of idiosyncratic R&D productivity of new entrants, and ψ is a parameter that scales all entrants' innovation probability.

In equilibrium, free entrance drives profits to zero, requiring the entrant firms to have sufficiently high innovating probability ($\underline{k}$) to stay in the market and try to innovate —we discuss the determination of the threshold of idiosyncratic productivity later in the section when we

[2] As we discuss in Section 5, we calibrate the quantitative model to ensure that the innovation probability $f_I(n_I)$ is between zero and one in all states of the economy.

derive the model equilibrium. Thus, the innovation probability for entrants is equal to:

$$f_E = \int_{\underline{k}}^{1} \psi k dk = \frac{\psi \left(1 - \underline{k}^2\right)}{2}, \quad \text{where} \quad 0 \leq \underline{k} \leq 1. \tag{1}$$

Expected growth rate of output. The expected, growth rate of output (g) in each sector weights the value of the innovated output with the probability of innovation from the incumbent firm and the entrant firms, thus being equal to:

$$g = \gamma \left(f_I + f_E\right).$$

3.2 The supply of research workers

The aggregatre supply of research workers in the economy is fixed to $\overline{L}$, and the labor supply ($L(w)$) in each sector is proportional to the sectoral-to-aggregate-wage ratio:

$$L(w) = \frac{\overline{L}}{J} \left(\frac{w}{W}\right)^{1/\epsilon}, \tag{2}$$

where J is the number of sectors, and w and W are the sectoral and aggregate wage indices, respectively, the latter taken as given by firms in each sector. The variable $\epsilon > 0$ is the inverse of elasticity of the labor supply for research workers that generates the standard, positively-sloped supply curve; i.e., $L'(w) > 0$.

The labor marker clears in each sector, such that the supply of researchers ($L(w)$) equates the demand from the incumbent and entrant firms, yielding:

$$L(w) = n_I + \left(1 - \underline{k}\right).$$

3.3 Equilibrium

The incumbent firm behaves strategically in hiring research workers since the established wage will influence the supply of researchers to the entrant firms and therefore their innovation probability, threatening the survival of the incumbent firm. Thus, the equilibrium in the model comprises two stages. In the first stage, the incumbent firm sets the prevailing wage for the sector, which determines the supply of researchers to the sector, and it then hires research workers at the end of the first stage. In the second stage, new entrants hire from the remaining pool of research workers taking the wage in the sector as given. No entrant has the incentive to deviate from the sectoral wage set by the incumbent firm, becaue a lower wage would lead to zero hiring, while a higher wage would decrease expected profit. To determine the equilibrium, we solve the model by backward induction, starting from the second stage.

Stage 2: Entry decision of the entrants

The potential new entrant enters the economy if the expected profit, $\psi k \gamma \pi - w$, is positive. The free entry condition drives the profits of firms to zero, determining the threshold of productivity ($\underline{k}\left(w\right)$) compatible with non-negative profits:

$$\underline{k}\left(w\right) = w / \left(\psi \gamma \pi\right). \tag{3}$$

By combining equations (1) and (3), we obtain the probability of successful innovation from the new entrant that triggers creative destruction:

$$f_E\left(w\right) = \psi \left[1 - \left(\frac{w}{\psi \gamma \pi}\right)^2\right] / 2, \tag{4}$$

which shows that the higher equilibrium wage reduces the measure of entry and suppresses the process of creative destruction by decreasing the profitability of new entrants.

Next, we show that no entrant has an incentive to deviate from the wage w set by the incumbent. First, all research workers have a job at the wage of w in equilibrium, so none of them is willing to accept any wage lower than w. As a result, there is no point for the entrant firm to set wages lower than w. Second, entrants also have no incentive to raise wages above w as it will only hurt their profits.

Stage 1: Wage setting of the incumbent

The incumbent firm chooses the number of research workers and set the wage to maximize the profits:

$$\max_{n_I,w} f_I\left(n_I\right)\gamma\pi + \left[1 - f_I\left(n_I\right) - f_E\left(w\right)\right]\pi - n_I w \tag{5}$$

subject to the equilibrium in the labor market:

$$n_I + \left[1 - \underline{k}\left(w\right)\right] = L\left(w\right). \tag{6}$$

In equation (5), $f_I\left(n_I\right)$ is the probability that the incumbent firm successfully innovates, obtaining the profit $\gamma\pi$. The second term encapsulates the profits when the innovations by the incumbent firm and the entrants are unsuccessful, which occurs with probability $1 - f\left(n_I\right) - f_E\left(w\right)$, obtaining the initial profit π. The third term is the wage cost for research labor. Between the second and the third term, there is a hidden term, $f_E(w)\cdot 0$, indicating that the incumbent firm leaves the market and obtains zero profit with creative destruction probability, $f_E(w)$.

Equation (6) is the clearance condition in the labor market that equates the demand and supply for research workers. It implies that n_I is a function of w, with $n_I\left(w\right) = \underline{k}\left(w\right) + L\left(w\right) - 1$. Since $L'\left(w\right) > 0$ and $\underline{k}'\left(w\right) > 0$, from equations (2) and (3), respectively, it yields:

$$n_I'\left(w\right) = \underline{k}'\left(w\right) + L'\left(w\right) > 0, \tag{7}$$

such that the hiring of the incumbent firm are positively related to the equilibrium wage, as stated in the next lemma.

Lemma 1. *The hiring of the incumbent firm increases with wage.*

Lemma 1 implies that the incumbent firm must hire more workers to increase the equilibrium wage, or, conversely, it must increase the wage to hire more workers.

Using equations (3) and (7), we obtain the impact of hiring by the incumbent firm on the entrance of new firms in the economy:

$$\frac{d\left(1-\underline{k}\right)}{dn_I}=-\frac{\underline{k}'\left(w\right)}{\underline{k}'\left(w\right)+L'\left(w\right)}<0, \tag{8}$$

where $1-\underline{k}$ is the measure of new entrants.[3] Equation (8) shows three important results. First, the increase in the hiring of research workers by the incumbent firm reduces the measure of new firms that enter the economy, giving rise to the motive of defensive hiring to be discussed soon. Second, the negative effect of the incumbent firm's hiring on new firm entry is stronger when the labor supply of researchers is inelastic (i.e., $L'\left(w\right)$ is low). Thus, the power of the incumbent firm to influence the number of new entrants decreases with the elasticity of labor supply of research workers. Third, the negative effect of the incumbent firm's hiring is stronger when the threshold productivity has a higher sensitivity to wage ($\underline{k}'\left(w\right)$). From equation (3) it is straightforward to show that the sensitivity increases when the expected profits from innovation (i.e., $\psi\gamma\pi$) are low.

The next proposition summarizes the results.

Proposition 1. *The hiring of research workers by the incumbent firm deters the entrance of new firms. The effect is stronger with inelastic labor supply and low expected profits from innovation for the entrants.*

3.4 Optimal conditions for the incumbent firm

Before solving the two-stage problem outlined in the previous section and deriving the equilibrium of the model, we study the equilibrium of the competitive and the classic monopsony markets, which will allow us to compare the equilibrium of the system to the equilibrium in the

[3] In particular,

$$\frac{d\left(1-\underline{k}\right)}{dn_I}=-\frac{d\underline{k}}{dn_I}=-\frac{d\underline{k}/dw}{dn_I/dw}=-\frac{\underline{k}'\left(w\right)}{\underline{k}'\left(w\right)+L'\left(w\right)},$$

where $dn_I/dw=\underline{k}'\left(w\right)+L'\left(w\right)$ comes from equation (7).

alternative competitive and monopsonistic markets.

Competitive market

In the competitive market, the incumbent firm takes the wage as given and set the level of employment to solve the following maximization problem:

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

which yields the standard optimal condition of the labor demand curve that equates marginal product of labor to wage:

$$\overbrace{w}^{\text{wage}} = \overbrace{\left(\gamma - 1\right) \pi f_I'\left(n_I\right)}^{\text{mpl}}.$$

Classic monopsony market

In the classic monopsonistic market, the incumbent firm internalizes the effect of wage on labor supply while taking as given the measure of entry $(1 - \underline{k})$, and the probability of creative destruction (f_E). The maximization problem of the incumbent firm becomes:

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

subject to:

$$n_I + (1 - \underline{k}) = L\left(w\right).$$

The key difference of the above constraint from equation (6) is that the classic monopsony incumbent firm does not internalize the influence of w on $1 - \underline{k}$ and f_E.

The first-order condition is:

$$\overbrace{w}^{\text{wage}} = \overbrace{\left(\gamma - 1\right) \pi f_I'\left(n_I\right)}^{\text{mpl}} - \overbrace{n_I\left(w\right) / L'\left(w\right)}^{\text{classic monopsony}}$$

The above condition shows that the incumbent firm reduces hiring (or, equivalently, cuts the wage) to increase profits since it internalizes that hiring introduces additional costs by increasing wages. The distortion due to the standard monopsony power is stronger when the labor supply is inelastic (i.e., when $L'(w)$ is low).

Benchmark model with strategic motives by the incumbent firm.

The incumbent firm in our model internalizes the effect of the equilibrium wage on the labor supply *as well as* the probability of creative destruction. By substitute n_I with $n_I(w) = L(w) + \underline{k}(w) - 1$ in equation (5), the incumbent's problem becomes:

$$\max_w f_I(n_I(w))(\gamma-1)\pi + [1 - f_E(w)]\pi - n_I(w)w.$$

The first-order condition is:

$$(\gamma-1)\pi f_I'(n_I)n_I'(w) - f_E'(w)\pi - n_I'(w)w - n_I(w) = 0$$

Applying equation (1), we re-write the above equation as:

$$\overbrace{w}^{\text{wage}} = \overbrace{(\gamma-1)\pi f_I'(n_I)}^{\text{mpl}} + \frac{\overbrace{\underline{k}(w)\underline{k}'(w)}^{\text{defensive hiring}} - \overbrace{n_I(w)}^{\text{classic monopsony}}}{\underline{k}'(w) + L'(w)} \tag{9}$$

The LHS of equation (9) is the wage. The first term on the RHS of equation (9), $(\gamma-1)\pi f'$ is the marginal product of labor (mpl) for the incumbent firm. The incumbent firm's incentive is distorted due to the incumbent firm's monopsony power, as reflected by the second term on the RHS of Equation (9), $\left(\underline{kk}' - n_I\right) / \left(\underline{k}' + L'\right)$. In the numerator of this term, $\underline{kk}'$ captures the incumbent firm's incentive of setting a higher wage (equivalently, hire more) to deter entry. This is effective because a higher wage raises the threshold of entry ($\underline{k}' > 0$), which reduces the probability of creative destruction. We refer to this as the *defensive hiring* incentive. n_I captures the incumbent firm's incentive of setting a lower wage (equivalently, reducing hiring), similar to the classic model of monopsony. We refer to this as the *classic monopsony* incentive. Whether the incumbent firm would set a higher or lower wage than in the competitive case depends on the relative strength of the two incentives.

Case 1: $\underline{kk}' > n_I$ When $\underline{kk}'$ is high, the incumbent finds it easier to "manipulate" the entrants' entry decision. When n_I is low, the incumbent firm is less concerned with the cost of the wage increase. As a result, when $\underline{kk}' > n_I$, the incumbent firm over-hires and sets a higher wage than in the competitive case, which leads to a lower firm entry. This effect is magnified when $L'(w)$ is low (which decreases the denominator of equation (9)): firm entry is further restrained when research labor supply is inelastic. In contrast, when the research labor supply becomes infinitely elastic ($L'(w) \to +\infty$), the distortion is diminished, and the model converges to the competitive case. Interestingly, our analysis shows that small incumbents are more likely to use defensive hiring than large incumbents, which might be opposite to many's presumptions.

Case 2: $\underline{kk}' < n_I$ As n_I is high, the incumbent firm is highly concerned with the wage cost. When $\underline{kk}'$ is low, the incumbent finds it more challenging to "manipulate" the entrants' entry decision. As a result, the classic monopsony incentive dominates, and the incumbent firm under-hires and sets a lower wage than in the competitive case, which leads to higher firm entry. Like Case 1, the effect is amplified when $L'(w)$ is low: firm entry is further promoted when research labor supply is inelastic.

The conditions for defensive hiring to dominate Whether $\underline{kk}'$ is higher than n_I depends on several factors. The first is the R&D production function of the incumbent firm, $\phi n_I^\alpha / \alpha$, which affects the level of n_I. If the incumbent firm's R&D productivity, ϕ, or the curvature parameter, α, is low, the optimal hiring n_I must also be low. As a result, the incumbent firm finds it less costly to raise wage, and defensive hiring is likely to dominate.

The second is the expected profit of innovation for the entrants, $\psi\gamma\pi$, which negatively affects

$\underline{k}$ and $\underline{k}'$ according to equation (3). When innovation is unprofitable for the entrants, both $\underline{k}$ and $\underline{k}'$ are high. In this case, the incumbent firm finds it easy to influence the entrants' entry decision, and defensive hiring is likely to dominate. The following proposition summarizes the above arguments.

Proposition 2. *The incumbent firm over-hires when (I), the incumbent's R&D productivity is low; (II), the incumbent firm has a strong degree of decreasing returns to scale in R&D; (III), entrants' expected profits from innovation is low. Moreover, the extent of over-hiring is stronger with inelastic labor supply.*

Proposition 2 outlines the conditions for defensive hiring to be the dominant force and shows that inelastic labor supply magnifies defensive hiring. Interestingly, conditions (I) and (III) in Proposition 2 are related to the notion of "ideas are getting harder to find" (Bloom et al., 2020), which implies that ψ and ϕ, i.e., the incumbent and entrants' R&D productivities, are decreasing, and therefore, conditions (I) and (III) in Proposition 2 are more likely to hold. In other words, our results indicate that defensive hiring will be more prevalent when ideas are getting harder to find.

4 Empirical evidence

This section establishes six new empirical findings. The first three facts estimate the elasticity of the labor supply of research workers, showing it is low on average, declines over time, and is heterogeneous across research fields and industries. The remaining three facts test the predictions of our theory, showing the effect of spending on R&D by incumbent firms on creative destruction and TFP growth: incumbent firms' R&D expenditure negatively predicts firm entry and industry productivity growth while increasing the life expectancy of incumbent firms. Consistent with the theory, we show these dynamics are stronger in industries with an inelastic supply of R&D workers.

4.1 The supply elasticity of research labor

Data on inventors and patents' value. We focus on the inventors who are a subset of research workers. We obtain information about inventors from patent application records constructed by the US Patent and Trademark Office (USPTO), which contains over seven million inventors and eleven million patent applications from 1970 to 2019.[4] These applications are categorized into 127 Cooperative Patent Classification (CPC) classes (e.g., Organic Chemistry), to which we refer as research fields. About 64-percent of the applications are successfully patented.

Our first goal is to measure inventors' allocation of research labor supply across different research fields. We denote the number of inventor ι's patent applications in year t as $m_t(\iota)$. We assume that inventors allocate research effort evenly across patents. Normalizing each inventor's yearly research effort to one implies that inventor ι spends $1/m_t(\iota)$ unit of labor on each patent.

Then we use $\Omega_{k,t}(\iota)$ to denote the subset of inventor ι's patent applications in field k. For patents that belong to multiple fields, we weight them by $1/n_i$, where n_i is the number of fields that patent i belongs to. Hence, by working on patent $i \in \Omega_{k,t}(\iota)$, inventor ι supplies $1/[m_t(\iota)n_i]$ to field k. An inventor's research labor supply to field k is thus computed as:

$$l_{k,t}(\iota) = \sum_{i \in \Omega_{k,t}(\iota)} \frac{1}{m_t(\iota)n_i}.$$

Finally, the total research labor supply to field k is the sum of $l_{k,t}(\iota)$ across inventors:

$$L_{k,t} = \sum_{\iota} l_{k,t}(\iota).$$

Our second goal is to study what determines an inventor's supply of research labor to a specific field. A natural candidate is the expected monetary payoff from research.[5] We assume that the monetary payoff for an inventor's research labor supply is proportional to the patent's

[4] We exclude the recent applications after 2019 as many of them have not been patented due to the long examination process.

[5] Other factors include the pure utility associated with interest, curiosity, gain of reputation, social responsibility, and so forth, which are hard to measure and are beyond the scope of this paper.

market value adjusted for the number of coinventors and the labor supply of these coinventors. This assumption can be justified by the fact that firm ownership, such as stocks and options, is an essential part of compensation for many researchers (e.g., machine learning engineers in tech companies). Moreover, the values of incentive pay (e.g., bonuses), promised wage raises, and promotion opportunities are likely to increase with the researchers' contribution to the companies' market value. With the above assumptino, the payoff per unit of research effort on patent i is:

$$w_i = \frac{v_i}{\left[\sum_{\iota \in \Phi_i} 1/m_t(\iota)\right]},$$

where v_i is patent i's real market value constructed by Kogan et al. (2017), based on how stock prices react to the announcement of patents by the USPTO. Φ_i is the set of coinventors of patent i. As discussed above, $1/m_t(\iota)$ is each coinventor's effort on patent i, and hence, $\sum_{\iota \in \Phi_i} 1/m_t(\iota)$ is the total effort across coinventors.

An alternative measure for the inventor's monetary payoff is inventors' wages, as considered by Akcigit and Goldschlag (2023) using tax data. While inventors' wages are an accurate measure for the contemporary "wage part" of the monetary payoff, they do not reflect changes in expected future income associated with the research effort, either in terms of promised wage raise or promotion opportunity, or the other nonwage compensation such as stocks and option, which are a critical component of inventors' monetary payoff and are likely to comove with (and hence, captured by) patent's market value. Hence we consider our measure complementary to Akcigit and Goldschlag (2023).

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

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

where $p_{k,t}$ is the fraction of applications that are successfully patented, which adjusts for the difficulty of patent application. $\Omega_{k,t}$ is the set of patents in field k. n_i is the number of fields that patent i belongs to. We weight patents by $1/n_i$ so that more focused patents (i.e., lower n_i)

receive heavier weights in a certain research field.

Fact 1. The research labor supply is inelastic on average

In this section, we investigate the relationship between the expected income from research and the labor supply in the extensive margin of research workers. We would like to explore the effect of a transitory increase in the market value of patents in a field like ORGANIC CHEMISTRY on the research labor supply in the field. To this aim, we estimate the following regression:

$$ln\left(L_{k,t}\right) = \alpha + \eta ln\left(W_{k,t}\right) + \chi_t + \gamma_k + \epsilon_{k,t}, \tag{10}$$

where $L_{k,t}$ is the total measure of research labor supply in research field k in year t. $W_{k,t}$ is the expected monetary payoff to research. Most fields experience increasing trends in the research labor supply and expected monetary payoff, which may differ across research fields and cannot be absorbed by a time-fixed effect. To make the series stationary, we detrend $ln\left(N_{k,t}\right)$ and $ln\left(W_{k,t}\right)$ with linear trends. χ_t is the year fixed effect. γ_k is the research field fixed effect, which purges out the long-run relationship between research labor supply and the expected monetary payoff to research, i.e., research fields constantly yield high (vs. low) payoff would always have high (vs. low) supply of researchers.

Shown in Column (1) of Table 1 is the full-sample estimation result. For a given research field, a one percent increase in the market value of patents is associated with about 0.05 percent more research labor supply. Interestingly, our point estimate for the inventors is much lower than the popular findings for the Hicksian elasticity (i.e., steady state elasticity) of the extensive margin labor supply that focuses on a much wider range of occupations.[6] For example, Chetty et al. (2011) find that a one percent permanent rise in wages would induce a 0.26 percent increase in the number of workers, where workers from all occupations are pooled in the estimation. The low value of our point estimate is intuitive since it takes a lot of time and effort for inventors to switch to a new research field, where a deep understanding of specialized knowledge is required

[6] See Chetty et al. (2011) for a comparison among different definitions of labor supply elasticities.

to innovate.

Fact 2. the elasticity of research labor supply is decreasing over time

To investigate how research labor supply elasticities evolve over time, we estimate equation (10) separately using data before and after 1995, respectively (1995 is about the middle of our sample).

Shown in Columns (2) and (3) of Table 1 are the estimation results. The coefficient of $ln\left(W_{k,t}\right)$ is estimated as 0.07 in the earlier subsample, much higher than the full sample result (0.05). In contrast, the point estimate is only 0.02, much lower in the later subsample. The results suggest that the research labor supply has been increasingly inelastic in recent decades. One possible explanation could be the deepening of specialization of research fields.

Table 1: The market value of patents and the number of inventors: panel estimation

	(1)	(2)	(3)
Periods	1970-2019	1970-1995	1996-2019
$ln\left(W_{k,t}\right)$	0.05***	0.07***	0.02**
	(0.01)	(0.01)	(0.01)
Research field FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Adj R-squared	0.86	0.93	0.67
Observations	5,997	2,917	3,080

The data is yearly for the period 1970-2019. The dependent variable is the log supply of research workers. The independent variable is the log expected value of patent applications.

Fact 3. The elasticity of research labor supply is heterogeneous across fields and industries

The elasticity of research labor supply might be different across research fields. Some research fields are more accessible for new entrants to catch up with the frontier knowledge and build new ideas, entailing a higher elasticity of research labor supply. In contrast, some other research fields are challenging for newcomers, at least in the short run, due to strong learning by doing that creates an advantage for incumbent researchers, knowledge structure unfamiliar to other fields, and so forth. These would entail a lower elasticity of research labor supply.

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

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

The coefficient of interest is η_k, which measures the elasticity of research labor supply for research field k. Panel (A) of Figure 3 plots the distribution of η_k across 127 CPC classes, which shows a strong heterogeneity of research labor supply elasticity among different fields. For example, Organic Chemistry has one the most elastic research labor supplies with $\eta_k = 0.74$. In contrast, Treatment of Nanostructures, Specific Uses, Applications, Measurement, Analysis, or Manufacture, have more inelastic research labor supply with $\eta_k = 0.003$, among fields with positive research labor supply elasticity. A few fields have negative research labor supply elasticity, which might be due to measurement errors.

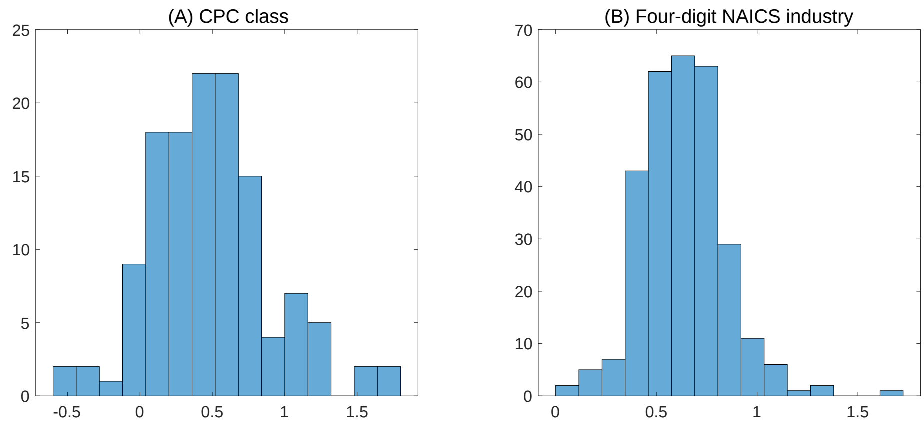
Different industries are exposed to research fields differently. For instance, the patents applied by companies in Nursing and Residential Care Facilities (a four-digit NAICS industry) are mostly concentrated in Organic Chemistry. The different exposure of industries to research fields implies that the research labor supply elasticities across industries are different. We measure the elasticity of research labor supply in industry j as:

$$\eta_j = \sum_k \omega_{j,k} \eta_k,$$

where $\omega_{j,k}$ is industry j's exposure to research field k, measured as the fraction of patents applied by firms from industry j that belong to field k, where $\sum_k \omega_{j,k} = 1$.[7] Panel (B) of Figure 3 plots the distribution of η_j across 31 four-digit NAICS industries. The result shows a strong heterogeneity of research labor supply elasticity among different industries.

[7]An alternative method of assigning weights is to use textual analysis in patent documents to gauge the technological components of industries. For example, Goldschlag et al. (2020).

Figure 3: Estimates for the elasticities of the labor supply of researchers across fields and industries



x-axis: The elasticity of the labor supply of researchers. Panel (A) estimates across fields (CPC classification); Panel (B) estimates across industries (four-digit NAICS industry classification). y-axis: frequency.

4.2 The effect of R&D by incumbent firms on firm entry and industry TFP

In the following part, we establish three key facts regarding the effect of the incumbent firms' R&D on firm entry and industry TFP. First, R&D expenditure prevents the entry of other firms into the same industry. Second, the increase in R&D expenditure by a firm decreases the sectoral productivity growth rate. Third, R&D expenditure increases a firm's life expectancy, which can be accounted for both by its positive effect on firm's productivity and its repression on potential competitors. For all three Facts, we show that the results are much stronger for industries with low elasticities of research labor supply.

Data on R&D, firm entry and TFP. We use three datasets to study R&D on firm entry and firm and industry TFP. Our primary firm-level dataset is Compustat Fundamental Annual data, which reports listed companies' sales, profit, employment, and R&D expenditure from 1950 to 2021. We focus on domestic companies and exclude international and multi-national companies, who report to operate at least one foreign segment. For those domestic companies, we replace negative R&D expenditure with zero, winsorize the top 1% of the R&D expenditure distribution, and add one unit to all companies' R&D expenditure. The last step changes zero R&D to one, which ensures that these observations would not be excluded when we take logarithm.

We obtain the sectoral TFP series from the Bureau of Labor Statistics (BLS) that provides yearly series for the period 1987-2019 covering 90 four-digit Naics industries (e.g., Plastics Product Manufacturing, etc.). Most of the four-digit industries are within the manufacturing sector.

Our primary dataset for firm entry is the Business Dynamics Statistics (BDS) administered by the US Census Bureau. BDS reports the number of firms for different age groups (from 0 to 26 years+) at the industry level. The data is yearly and covers 281 four-digit Naics industries for the period 1978-2019. We treat firms with zero-age as new entrants and compute the entry rate as their share in all firms.

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

Table 2: Incumbent R&D expenditure and firm entry: panel estimation

	(1)	(2)	(3)	(4)
Dependent variable	Entry rate, BDS		Listing rate, Compustat	
$R\&D_{j,t}$	-0.76***	-2.45***	-1.39***	-2.45***
	(0.07)	(0.20)	(0.08)	(0.19)
$R\&D_{j,t} \times \eta_j$		3.24***		1.33***
		(0.37)		(0.33)
Industry FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Adj R-squared	0.82	0.83	0.61	0.62
Observations	1339	1,339	1,696	1,677

The data is yearly for the period 1970-2019. The dependent variable is the rate of entry. The independent variable, *R&D*, is the average R&D expenditure across incumbent firms. η is the elasticity of research labor supply.

In this section, we study the relationship between incumbent R&D and new firm entry. Our benchmark measure of entry rate is the share of newly created firms for all firms in BDS data. We estimate the following regression at the four-digit NAICS industry level:

$$Entry_{j,t+5} = \alpha + \beta R\&D_{j,t} + \gamma_j + \chi_t + \epsilon_{i,j,t}, \tag{11}$$

where the dependent variable, $Entry_{j,t+5}$, is industry j's average entry rate from $t+1$ to $t+5$. $R\&D_{j,t}$ is industry j's the logarithm of the total R&D expenditure of incumbent firms from industry j. γ_j and χ_t are industry and year fixed effects. Shown in Column (1) of Table 2 is the estimation result. A percentage increase in incumbent firms' R&D predicts a 0.76 percentage drop in the yearly rate of firm entry of the same industry in the following five years, an economically significant impact.

Next, we investigate the role of research labor supply elasticity in the impact of incumbent firms' R&D on firm entry by including an interaction term, $R\&D_{j,t} \times \eta_j$, as an independent variable. Column (2) shows the results. The coefficient of the interaction term is estimated as positive, indicating a more negative relationship between incumbent firms' R&D and firm entry for industries with inelastic research worker supply (i.e., η_j is low). For example, a percentage increase in incumbent firms' R&D expenditure is associated with -2.45% slower firm entry rate in the following five years if research labor supply is completely inelastic, i.e., $\eta_j = 0$. In contrast, the relationship becomes less negative, or even positive, for industries with high η_j.

Finally, we examine whether listed companies' R&D negatively affects the rate of listing of the same industry at the stock exchange, which reflects grow opportunity of unlisted firms that are likely younger and smaller. To this aim, we replace the dependent variable of equation 11 with the average rate of listing (the ratio of new listing to the total number of listing) in the following five years. Shown in Columns (3) and (4) of Table 2 are the estimation results. Higher R&D of incumbent firms predicts slower listing of firms. The result is stronger for industries with inelastic research worker supply, as invinced by the positive estimate of the interaction term. The results show that R&D expenditure of listed companies makes their competitors more difficult to become publicly traded companies, particularly in industries where research labor supply is inelastic.

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

In the following part, we show that incumbent R&D negatively predicts productivity growth of other firms in the same industry in industries with low research labor supply elasticity.

Table 3: Incumbent R&D expenditure and sectoral productivity: panel

	(1)	(2)	(3)	(4)
Dependent variable	$\Delta z_{-i,j,t+5}$		$\Delta z_{j,t+5}$	
$R\&D_{i,j,t}$	-0.06	-0.61***		
	(0.07)	(0.22)		
$R\&D_{i,j,t} \times \eta_j$		0.98***		
		(0.37)		
$R\&D_{j,t}$			-0.01***	-0.04***
			(0.004)	(0.01)
$R\&D_{j,t} \times \eta_j$				0.05***
				(0.02)
Industry FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Adj R-squared	0.09	0.09	0.55	0.56
Observations	40,359	40,331	587	587

The data is yearly for the period 1970-2019. The dependent variable is the productivity growth rate in percentage points. The independent variable, $R\&D$, is the R&D expenditure. η is the elasticity of research labor supply.

We first investigate the spillover effect of listed companies' R&D on the productivity growth of other listed companies in the same industry. In particular, we estimate the following regression at the firm level:

$$\Delta z_{-i,j,t+5} = \alpha + \beta R\&D_{i,j,t} + \gamma_j + \chi_t + \epsilon_{i,j,t}, \tag{12}$$

where the key independent variable, $R\&D_{i,j,t}$, is the logarithm of listed company i's R&D expenditure. The dependent variable, $\Delta z_{-i,j,t+5}$, is the labor productivity growth of listed companies in industry j except for company i from t to $t+5$. In particular, the average labor productivity of listed companies in industry j except for company i is computed as:

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

where $\Psi_{k,t}$ is the set of listed companies in industry j with employment measurements. $y_{i',j,t}$ and $l_{i',j,t}$ is company sales and employment. Then $\Delta z_{-i,j,t+5}$ is computed as $(z_{-i,j,t+5}/z_{-i,j,t} - 1)/5$.

Shown in Column (1) of Table 3 is the estimation result. R&D expenditure of a listed company is not significantly correlated with other listed companies' labor productivity growth. The insignificant result can be a result of two counteractive forces. On the one hand, a firm's R&D can have negative spillover effects on other firms' productivity growth by squeezing the availability of research workers when they are scarce resources. On the other hand, a firm's R&D can also benefit other firms' productivity growth via a conventional knowledge spillover channel, particularly when they have close technological proximity (Bloom et al., 2013). However, we show that the former negative spillover effect dominates for industries with inelastic research labor supply.

Specifically, we examine the role of research labor supply elasticity in the spillover effect of firms' R&D on other firms' productivity growth, by including an interaction term, $\eta_j \times R\&D_{i,j,t}$), as a regressor. Shown in Column (2) of Table 3 is the result: the positive coefficient of the interaction term indicates that a firm's R&D has a more negative spillover effect on the other firms' productivity growth when the industry has a lower research labor supply elasticity. For example, a percentage increase in R&D expenditure by a listed company is associated with 0.61 percent slower labor productivity growth of other listed companies when research labor supply is completely inelastic, i.e., $\eta_j = 0$, much stronger and more statistically significant than our unconditional estimate in Column (1).

Given that incumbents' R&D negatively predicts other incumbents' productivity growth and deters firm entry in industries with research labor supply is inelastic, it is natural to conjecture that incumbent firms' R&D negatively predicts industry's TFP growth for these inelastic industries. To this aim, we estimate the following regression at the four-digit NAICS industry level:

$$\Delta z_{j,t+5} = a + bR\&D_{j,t} + c\eta_j \times R\&D_{j,t} + \gamma_j + \chi_t + \epsilon_{j,t}, \tag{13}$$

where the dependent variable, $\Delta z_{j,t+5}$ is industry j's yearly TFP growth from t to $t+5$ constructed by the BLS. $R\&D_{j,t}$ is the logarithm of total R&D expenditure of listed companies from industry j. Shown in Columns (3) and (4) of Table 3 are the results. Column (3) indicates that R&D expenditure of listed companies negatively predicts the industry's TFP growth. A percentage increase in listed companies' R&D expenditure is associated with a 0.01 percent decline in the industry's yearly TFP growth in the following five years. Column (4) shows that the negative relationship between listed companies' R&D expenditure and industry TFP growth is much stronger for industries with low research labor supply elasticity. For example, a 1% increase in listed companies' R&D expenditure is associated with a 0.04 percent decline in the industry's yearly TFP growth when research labor supply is completely inelastic, i.e., $\eta_j = 0$, four times stronger than the unconditional estimate in Column (3).

The above result might seem the opposite to the prototypical finding in the literature that posits R&D as the principal driver of economic growth. There are two caveats when interpreting our result. First, our regression model misses the positive spillover effects of R&D *across* industries, which has been found sizable and critical in accounting for the benefit of R&D on economic growth. Second, we include industry fixed-effects, which filter out the stable and positive relationship between R&D and productivity growth *across* industries. If we remove the industry-fixed effects from our estimation, the coefficient of R&D becomes positive. This is consistent with Jones and Williams (1998), who document that the positive relationship between R&D and productivity growth crucially depends on their long-run cross-industry comovement.[8]

Fact 6. Incumbent R&D increases firm's life expectancy for industries with inelastic research labor supply

Finally, given the adverse role of incumbent firms' R&D on their competitors' entry, public listing, and productivity growth, it is natural to conjecture that R&D increases incumbent firms' life expectancy, which is one of the incumbent firms' most significant concerns and the biggest motivation for defensive hiring. We test the above hypothesis by estimating the following

[8] They show that the correlation between $R\&D$ and productivity growth is not significant positive once controling for industry-fixed effects (see their footnote 14 on page 1131).

cross-sectional regression at the firm level:

$$LifeExp_{i,j} = \alpha + \beta R\&D_{i,j} + Rvn_{i,j} + \gamma_j + Birth_{i,j} + \epsilon_{i,j}, \tag{14}$$

where the dependent variable, $LifeExp_{i,j}$, is the life expectancy of listed company i from industry j, computed as the number of years between its listing and delisting years. $R\&D_{i,j}$ is the logarithm of company i's average R&D expenditure. $Rvn_{i,j}$ is the logarithm of company i's average sales, which controls for the effect of size on life expectancy. To compare companies within the same industry and listed in the same year, we also control for the industry fixed effect, γ_j, and the fixed effect for companies' listing year, $Birth_{i,j}$. To be consistent with the time period of our research labor elasticity measure, we focus on companies listed after 1970 (when our patent data starts) and delisted before 2019 (when our patent data ends).

Column (1) of Table 4 shows that increasing a company's R&D expenditure by 10% would extend the company's life expectancy by 0.037 (0.1×0.37) years. Given that the median R&D to sales ratio is 0.11, the cost of the above action is about 1.1% of annual sales. The following calculation quantifies the increase in life expectancy as a part of private return on R&D. The average ratio of profit-to-sales ratio in our estimation sample is 0.08. Increasing R&D expenditure by 10% would enable a company to earn a profit that is about 0.30% (0.08×0.037) of its annual sales, about 27.3% (0.30%/1.1%) of the R&D cost by enjoying longer life expectancy..[9]

Column (4) of Table 4 shows the results when we include the interaction term, $\eta_j \times R\&D_{i,j}$, as a regressor. The coefficient of the interaction term is negative, which implies that R&D has a higher (lower) effect on companies' life expectancy in industries with a lower (higher) elasticity of research labor supply. Intuitively, in industries with an inelastic research labor supply, it is easier for incumbent firms to take advantage of their monopsony power in protecting their businesses against creative destruction. Using the proceeding calculation, in an industry with completely inelastic research labor supply elasticity, $\eta_j = 0$, increasing R&D expenditure by 10% would enable a company to earn a profit that is about 48.7% of the R&D cost by enjoying longer

[9] In this calculation, we assume that the discount rate is similar to the sales growth rate.

life expectancy.

Table 4: Incumbent R&D expenditure and life expectancy of the incumbent firm: cross-sectional analysis

	(1)	(2)
Dependent variable	Life expectancy	
$R\&D_{i,j}$	0.37***	0.66***
	(0.05)	(0.13)
$R\&D_{i,j} \times \eta_j$		-0.50**
		(0.21)
Revenue	0.40***	0.40***
	(0.04)	(0.04)
Industry FE	Yes	Yes
Cohort FE	Yes	Yes
Adj R-squared	0.42	0.42
Observations	7,429	7,392

The data is yearly for the period 1970-2019. The dependent variable is the life expectancy of the incumbent firms. The independent variable, *R&D*, is the logarithm of average R&D expenditure. η is the elasticity of research labor supply. *Revenue* is log of average revenues from sales.

5 Quantitative model

This section develops an extended version of our simple model to study quantitive implications and policy analysis. TBA

6 Conclusion

Our analysis shows theoretically and empirically that the interplay between monopsony power in the market for research workers and the inelastic supply of these workers across fields and industries is a key driver for the contrasting persistent decline in creative destruction and productivity growth occurring together with the substantial increase in R&D spending (both headcount and retribution of researchers) in the US economy over the past twenty years.

Our novel theory shows that these seemingly contrasting forces arise from the strategic behavior of the incumbent firms that internalize the effect of hiring research workers for the probability of competitors to innovate. In monopsony markets, this strategic behavior leads the incumbent firms to optimally undertake what we called "defensive hiring" and overhire talents to deter innovation from the entrant firms and preserve market dominance. This mechanism operates and is magnified by the relatively inelastic supply of research workers.

We empirically assess our mechanism and test the theoretical predictions of the model on creative destruction and productivity growth by assembling a novel dataset that combines information on inventors from the universe of patent applications in the US, linking researchers to the stock market values of their inventions, the spending on R&D by incumbent firms and the rate of entrance of new firms across 281 four-digit Naics industries. The novel dataset empirically validates the predictions of our theory, showing that the elasticity of the supply of researchers is low (equal to 0.05 on average) and it has steadily declined since the mid-1990s (to 0.02); spending on R&D by incumbent firms is negatively related to the rate of creative destruction and the growth of sectoral TFP, while increasing the life expectancy of incumbent firms. Furthermore, these relationships are stronger in industries with inelastic supply of R&D workers, consistent with the predictions of our theory.

An extended version of our simple model outlines the quantitative relevance of our mechanism for productivity growth, creative destruction, and economic policy. TBA.

Our analysis points to several fruitful extensions for future research. Our theory attributes a central role to the inelastic labor supply of researchers, which several studies point to as an inevitable consequence of modern production that requires highly specialized knowledge. Specialization hinders the mobility of researchers across fields but increases innovation capabilities. Measuring the specialization of knowledge, documenting its variations over time and across research areas, and using these dimensions to investigate the implication of knowledge specialization to technological growth in an era of high monopsony power in the labor market would certainly be an important next step. Another fruitful extension would be to consider the design of the education system and the study of educational policies. Specifically, would an inter-disciplinary approach to education facilitate the movements of researchers across fields and industries? Would the advancement in online education, remote working, or a different organization of knowledge-sharing practices overturn the current depressing forces on TFP and creative destruction? These important questions remain open to future research.

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