R&D Return Dispersion And Economic Growth — The Case of Inventor Market Power*

Nils H. Lehr†

Boston University

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Abstract

This paper documents large and persistent differences in R&D returns across listed US firms, with firms at the 75th percentile having twice the median return. Systematic R&D return differences are surprising as workhorse endogenous growth models predict that R&D resources flow from low to high returns firms until return equalization, maximizing aggregate R&D productivity. I then document a strong, positive correlation of R&D returns with inventor employment, which points to monopsony power as a potential driver of R&D return dispersion. I show that heterogeneity in firms' market power over inventors leads to R&D return dispersion in theory and provide evidence in favor of this hypothesis. My estimates suggest that firms with high returns and those with a large inventor workforce face less elastic inventor supply, giving them more inventor market power. Calibrating a Schumpeterian growth model to match this evidence, I find that inventor monopsony can account for 1/3 of the documented R&D return dispersion. Removing this distortion would increase the growth rate by 0.06 p.p. and raise welfare by 2.1% in consumption equivalent terms.

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†Email: nilslehr@bu.edu Mailing Address: Boston University, Dept. of Economics, 270 Bay State Rd., Room 515, Boston, MA 02215.

1 Introduction

Economic growth is the engine of rising living standards and welfare in the long-run. In modern economic growth theory, the growth-rate of an economy is the product of the resources invested in creating growth, research and development (R&D) expenditure, and R&D productivity, i.e. the rate at which these resources are translated into economic growth:

$$\text{Growth} = \text{R\&D Expenditure} \times \text{R\&D Productivity}.$$

In economies where most R&D expenditure is performed by the private sector, such as the US, aggregate R&D productivity crucially depends on the allocation of R&D resources across firms.[1] In turn, firms' incentive to conduct R&D, and thus their demand for R&D resources, is intimately linked to the resulting return on their investment, the R&D return:

$$\text{R\&D Return} = \frac{\text{Value created from R\&D}}{\text{Cost of R\&D}}.$$

Firms with high returns have an incentive to expand their R&D activity to take advantage of the opportunity for value creation and vice versa. In models with frictionless and competitive input markets, including the workhorse endogenous growth models, this force is sufficiently strong that R&D returns are equalized across firms in equilibrium.[2] Firms with above equilibrium return expand their R&D activity until dimishing returns push their returns back towards the equilibrium level. As long as social and private returns are aligned, the resulting allocation maximizes the economy's R&D productivity.

In this paper, I document that measured R&D returns are highly dispersed across US listed firms and persistently so. I measure R&D return as the ratio of patent valuations to R&D expenditure and find that a firm at the 75th percentile earns twice the median return. Return differences are highly persistent: the same firm retains a return 65% larger than the median after 5 years. The documented dispersion is large in relative terms, exceeding return on capital dispersion by 40%. I find that R&D returns continue to be highly dispersed across alternative specifications, measurement approaches, and structural or bootstrapping-based measurement error adjustments. This finding thus poses the question as to the potential economic drivers of R&D return dispersion and their implications for economic growth.

[1] According to the NSF National Patterns, the average share of R&D performed by business between 1975 and 2020 is 71%. The average share of R&D funded is slightly lower at 59% and has been steadily increasing.

[2] See e.g. Romer (1990), Aghion and Howitt (1992), and Acemoglu and Cao (2015) as well as the models covered in Gancia and Zilibotti (2005) and Aghion et al. (2014).

Taking a closer look at the data, I find that firms investing heavily in innovation tend to earn high returns, and vice versa. For example, Apple and Qualcomm rank in the Top 50 of long-run R&D returns, while Ford and General Motors rank in the bottom 50. These examples suggest that prominent sources of return on capital dispersion such as financial frictions or investment subsidies might not be as important in this context. Indeed, I find that proxies for financial frictions, including the return on capital, and R&D subsidies are uncorrelated with R&D returns. In contrast, I uncover a strong, positive correlation between inventor employment and R&D returns.

One potential channel giving rise to such a relationship is monopsony power in the market for inventors. Monopsony power can arise when individual firms account for a significant share of demand for particular types of labor, which is especially likely to occur in highly specialized labor markets such as those for inventors, and are thus able to influence their wages. Under this mechanism, firms facing less elastic inventor labor supply, i.e. those whose wages are particularly responsive to their demand for inventors, suppress their hiring relative to a competitive benchmark to keep wages low. Resultingly, these firms have to scale back their R&D activity and, by virtue of diminishing returns, achieve higher R&D returns. I estimate that differences in the labor supply elasticity can account for 30% of the return difference between firms with above and below median R&D return. Furthermore, I find that inventor supply is less elastic for firms with large inventor workforce, which can explain why these firms also tend to have larger R&D returns. Thus, R&D return dispersion might not be a failure from firms' perspective, but a signal that firms' monopsony power over inventors affects the allocation of R&D in the US and, thus, potentially economic growth.

I estimate the impact of inventor monopsony on R&D return dispersion and economic growth in a calibrated Schumpeterian growth model. In the model, firms with heterogeneous R&D productivity hire inventors subject to a firm-specific inventor supply elasticity that declines with inventor employment as suggested by my evidence and proposed in Card et al. (2018). Intuitively, the firm-specific labor supply formulation captures that firms hiring many inventors face increasingly thin markets and, thus, have to bid aggressively to attract the desired inventor workforce. I calibrate the model using a combination of parameters chosen from either the literature or moment matching, where I discipline the parameters governing firm labor supply using evidence on inventor's labor supply differences. The model suggests that inventor monopsony can account for 1/3 of the documented R&D return dispersion. Removing this distortion increases in the annual growth-rate of 0.06 p.p. (4%) and raises welfare by 2.1% in consumption-equivalent terms. For comparison, Berger et al. (2022) estimate the cost of labor monopsony in the production sector at 7.6%. More generally, Lucas (2003) and Arkolakis et al. (2012) estimate that the welfare cost of business cycles and trade autarky for the US are around 1%. Importantly, faster growth is entirely due to a reallocation of inventors from low to high R&D productivity firms and, thus, reflects an improvement in aggregate R&D productivity rather than an expansion of R&D investment.

Literature. This paper contributes to three strands of the literature. First, my findings add to the literature on resources allocation in endogenous growth models. The existing literature focuses primarily on the misalignment of private and public incentives in R&D, which can give rise to dispersion in public, but not private, R&D returns. A first generation of models assumed competitive markets for R&D inputs and that inventors have the same markups (Romer, 1990; Aghion and Howitt, 1992; Acemoglu and Cao, 2015). For example, Gancia and Zilibotti (2005) survey a lab equipment models where new ideas are created in a frictionless way from the final good. In these papers, R&D returns are equalized, and because of common markups, social returns are also equalized. The resulting allocation maximizes aggregate R&D productivity. A recent set of papers explores the implications of different markups driven by differences in quality or process efficiency (Acemoglu et al., 2018; de Ridder, 2021; Aghion et al., 2022b,a).[3] In these papers, social returns and private returns are not proportional and the allocation of R&D inputs does not maximize R&D productivity nor growth. However, in these papers, markets for R&D inputs are competitive and so private returns are equalized. I contribute to this literature by highlighting the importance of frictions in the market for R&D inputs, especially inventors, as evidenced by the large documented dispersion in private R&D returns.[4] My companion paper provides formulas explicit for aggregate R&D productivity (Lehr, 2022).

Second, the documented R&D return dispersion speaks to the literature on factor misallocation. (Restuccia and Rogerson, 2008) and Hsieh and Klenow (2009) first documented large factor return dispersion in the production sector, similar to what I find for the R&D sector, and attributed it to misallocation. Recent advances link dispersion in the return on capital to financial frictions and risk, while I find these forces to be of lesser importance for

[3] Terry et al. (2022) and Terry (2022) consider models in which agency frictions drive diverging private and social returns.

[4] Akcigit et al. (2022) also consider frictions when investigating the optimal design of R&D tax credits. They calibrate frictions in a reduced form using the ratio of sales changes to R&D expenditure.

R&D return dispersion (Midrigan and Xu, 2014; David et al., 2021).[5] Similarly, Hsieh and Klenow (2009) argue that the factor return dispersion partly reflects government intervention, while I find little evidence for R&D subsidies driving R&D returns.[6] Finally, I focus on the R&D sector instead of the production sector. This distinction is conceptually important as the allocation of resources in the production sector affects the productivity level, while the allocation in the R&D sector affects the productivity growth rate. This distinction is also highlighted in the companion paper Lehr (2022), which builds a canonical growth model and derives an explicit formulation of the growth rate depending on reduced form frictions, similar to the result for the production sector in Hsieh and Klenow (2009). Interpreted as reduced form frictions, dispersion in the R&D return reduces the productivity growth rate of the economy, while dispersion in the return on capital reduces the productivity level.

Third, my paper is closely related to the growing literature on labor market frictions, which documents pervasive monopsony power in the production sector (Azar et al., 2019; Lamadon et al., 2022; Schubert et al., 2022).[7] Importantly, the literature finds monopsony to be particularly strong for high-skilled workers, which arguably include many inventors (Prager and Schmitt, 2021; Seegmiller, 2021; Friedrich et al., 2021). I extend the findings in this literature to a new context: inventors. Following the estimation strategy in Seegmiller (2021), but focusing on inventors instead of employees in general, I estimate that firms have significant monopsony power.[8] Furthermore, my estimates suggest that monopsony power is especially strong for firms with larger inventor workforce, echoing findings in Berger et al. (2022); Yeh et al. (2022) for the production sector. Motivated by this evidence, I introduce size-dependent monopsony a la Card et al. (2018) into a quantitative endogenous growth model. In the calibrated model, inventor monopsony significantly reduces aggregate R&D productivity and economic growth by altering the allocation of inventors across firms.

Structure. Section 2 introduces the data used in Section 3 to document R&D return dispersion. Section 4 inventor market imperfection empirically, while Section 5 estimates their impact on economic growth in a quantitative Schumpeterian model. Section 6 concludes.

[5] Brown et al. (2009) and Ewens et al. (2020) argue that financial frictions are particularly severe for intangible capital, which is closely connected to R&D. However, I am unable to find strong correlations of R&D returns with proxies for financial frictions.

[6] Additional sources of factor return dispersion identified by the literature include informations frictions, adjustment cost, and markups (Asker et al., 2014; David et al., 2016; David and Venkateswaran, 2019).

[7] There is also some evidence that non-compete contracts limit worker mobility, which is another source of firm market power over employees (Shi, 2020).

[8] Kline et al. (2019) provide evidence that successful patent applications result in higher wages for skilled workers, while my results speak more directly to the hiring decisions faced by firms.

2 Data

My data combines information on the financial performance and innovations of US listed firms. I obtain financial for US listed firms from WRDS Compustat, who collect them from mandatory filings by the company and harmonized them. The data reaches back to 1959 and its availability is tied to the company's listing status. Variables of interest include R&D expenditure (`xrd`), sales (`sale`), capital stock (`ppent`), and employment (`emp`).

I measure firms' innovation from their new patents, which I record in their application year. My main measure are the patent valuations from Kogan et al. (2017), who estimate them based on the firm's stock market returns around the patent announcement by the US Patent and Trademark Office (USPTO). Patents are arguably the most direct measure of R&D output available to researchers. A patent captures an invention that the issuing patent office, here the USPTO, deemed new and useful, and grants the owner exclusive rights to the use of the invention described therein. These rights give firms strong incentives to patent inventions, making the value of newly granted patents a direct measure of their innovation output.[9] Patent valuations, in turn, capture the private value of an invention, which is directly linked to firms' incentives to innovate. In contrast, other patent-based measures of innovation such as (citation-adjusted) patent counts capture the quantity of innovation, but not necessarily its value to the firm.[10]

I measure inventor employment, which is important for my analysis on labor market imperfections, using patent records. I identify and link inventors across patents using the USPTO's disambiguation. I then assign them to the firm based on whether they are listed on a firm's newly-granted patent within the relevant 5-year window. I assign the firm a full time equivalent share of the inventor based on the firm's share in the inventor's new patent portfolio and aggregate to the firm-level by summing over all inventors.

I restrict the sample to 1975-2014 and drop firms with consistently low R&D expenditure (less than 2.5m 2012 USD per year), low patenting (less than 2.5 patents per year) or less than 5 sample years. The final sample covers more than 80% of R&D expenditure in Compustat and patent valuations in Kogan et al. (2017) for the 1975-2014 period as well as 40% of the R&D recorded in BEA accounts. See Appendix A for further data details.

[9] Not all inventions are patented (Cohen and Klepper, 1996). Thus, patents remain an imperfect measure.

[10] These concepts can diverge e.g. due to externalities or because some firms are better equipped than other to take advantage of an invention. See e.g. Lerner (1995); Bloom et al. (2013); Kogan et al. (2017); Akcigit and Kerr (2018a); de Ridder (2021); Kelly et al. (2021); Aghion et al. (2022b)

3 Documenting Return on R&D Dispersion

This section introduces the measurement of R&D returns, documents their dispersion, and discusses potential drivers thereof through the lens of a canonical endogenous growth model.

3.1 Measurement

I define the R&D return as the ratio of the value created from R&D divided by its cost. Conceptually, we can attribute variation in this measure to two potential sources: variation in the expected returns at the time of investment, and variation around this value once the associated projects are completed and their value is revealed. While the former is informative about the R&D decision-making process, the latter primarily speaks to the extend of uncertainty in innovation. In this paper, I focus on the R&D decision making process and, hence, construct measures of expected R&D returns. I will measure costs from R&D expenditure, and, as discussed above, R&D output using patent valuations.

I measure the Expected Return on R&D for firm i in year t as the ratio of patent valuations to previous year's R&D expenditure at the 5-year horizon:

$$\texttt{Expected R\&D Return}_{it} \equiv \frac{\sum_{s=0}^{4} \texttt{Patent Valuations}_{it+s}}{\sum_{s=0}^{4} \texttt{R\&D Expenditure}_{it-1+s}}. \tag{1}$$

I drop observations based on less than 50 patent valuations. The median (average) return has around 160 (520) underlying patent valuations. Focusing on an extended horizon with many underlying patents allows me to measure ex-ante expectations if the law of large numbers applies in this context.[11] My final sample has around 12,000 returns from 900 firms.

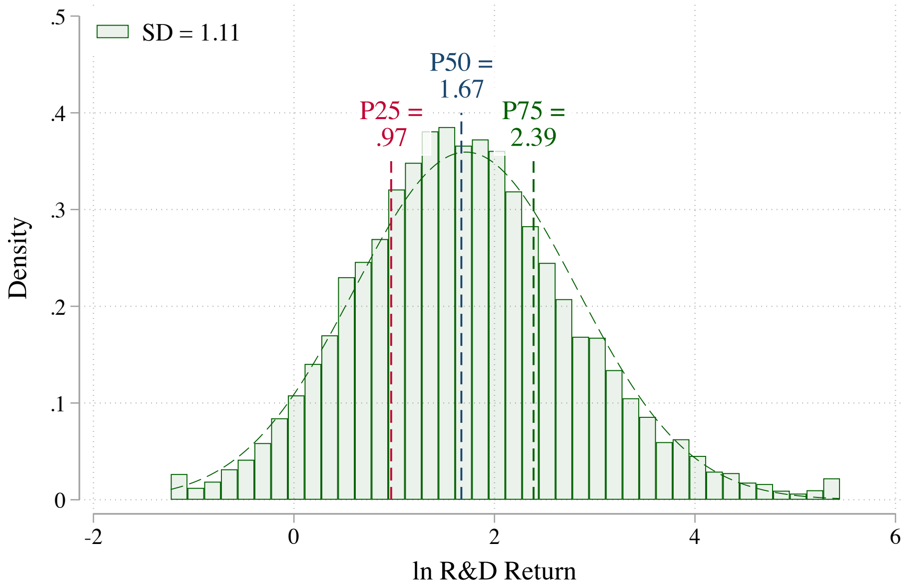
3.2 R&D Return Dispersion

Expected R&D returns are highly dispersed as documented in the histogram in Panel (a) of Figure 1. A firm at the 75th percentile of the distribution earns approximately twice the median return with a similar gap between the median and 25th percentile.[12] The standard deviation of the log expected R&D returns is 1.1.

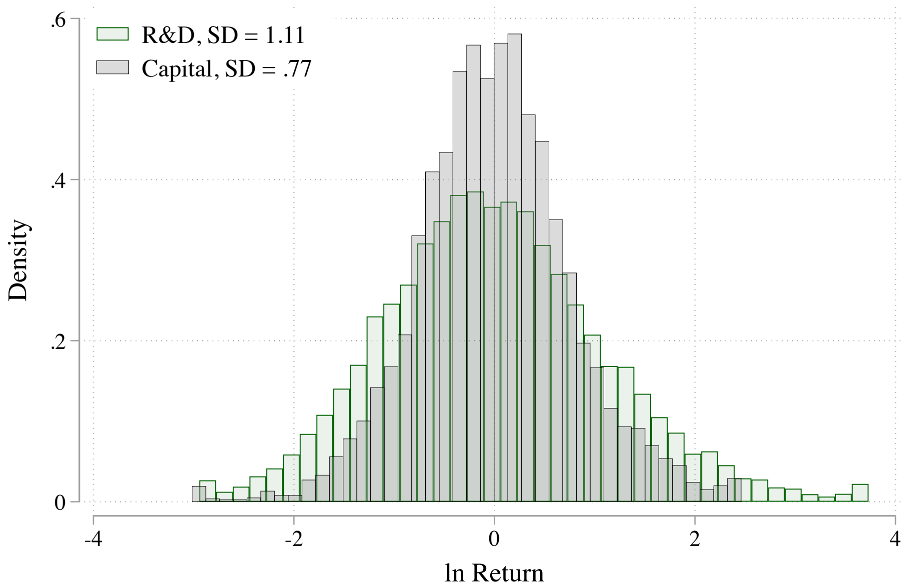
[11] Note, however, that patent valuations are tied to USPTO patent grant announcements, which occur on a weekly basis. The minimum different announcement weeks for a return in my sample is 28 with a median (average) of 117 (159).

[12] In particular, $\exp(2.39 - 1.67) \approx 2$ and $\exp(1.67 - 0.97) \approx 2$.

Figure 1: Expected R&D Returns are Highly Dispersed



(a) Histogram of R&D Returns



(b) Histogram of R&D Returns and Return on Capital

Notes: Panel (a) plots the histogram of the log expected R&D returns and density function of a normal distribution with same the first and second moment. Panel (b) plots histogram of demeaned log expected R&D returns and return on capital. SD refers to the standard deviation. R&D returns are measured as the 5-year total patent valuation divided by 5-year R&D expenditures lagged by one year. Capital returns are defined as 5-year sales divided by 5-year beginning of period capital stock. See Section 2 and Appendix A for data detail.

I benchmark the measured dispersion using the return on capital, which is an interesting comparison as a large literature argues that its dispersion is quantitatively large and an indicator for capital misallocation with significant cost for production efficiency.[13] Following David et al. (2021), I measure the return on capital as the ratio of sales to beginning of period capital stock. As for the R&D return, I construct the measure at the 5-year level:

$$\texttt{Return on Capital}_{it} \equiv \frac{\sum_{s=0}^{4} \texttt{Sales}_{it+s}}{\sum_{s=0}^{4} \texttt{Capital}_{it+s}}. \tag{2}$$

R&D return dispersion is significantly larger than disperison in the return on capital. As reported in the histogram in Panel (b) of Figure 1, the standard deviation R&D returns it is about 40% larger than its counterpart for the return on capital.[14] Dispersion in R&D returns thus appears to be large both in absolute and relative terms. Before exploring the theory around R&D return dispersion, I briefly highlight the robustness of this finding.

3.3 Robustness

Throughout numerous robustness exercises I find that R&D returns continue to be highly dispersed and significantly more so than the return on capital. Appendix B.1 documents that R&D return dispersion is robust to alternative specifications of R&D returns and approaches to measuring R&D inputs or outputs. Appendix B.2 discusses two independent strategies to estimating measurement error, which both fail to attribute a significant share of R&D return dispersion to measurement error. Here, I want to briefly highlight two features of the data that are particularly informative about the nature of R&D returns dispersion.

First, R&D returns are highly auto-correlated. As reported in column (1) of Table 1, the 5-year auto-correlation of R&D returns is 0.7, implying a 1-year coefficient of $0.7^{1/5} \approx 0.93$.[15] As reported in columns (2)-(4), this finding extends to alternative measures of R&D returns, which are explained in detail in Appendix B.1, and suggests that R&D returns capture a persistent phenomenon at the firm level instead of independent events across time.

[13] Theory predicts that the return on capital should be equalized across firms as capital flows from low to high return firms to maximize overall returns. Dispersion is then a sign of inefficient investment allocation. See e.g. Restuccia and Rogerson (2008); Hsieh and Klenow (2009, 2014); David et al. (2016).

[14] This difference is highly statistically significant as standard errors for both SDs are smaller than 0.02.

[15] Estimating auto-correlation at the 5-year window avoids mechanical correlation due to the measurement of R&D returns.

Table 1: R&D Returns Are Highly Autocorrelated

	(1)	(2)	(3)	(4)
		R&D Return$_{it}$		
R&D Return$_{it-5}$	0.699***	0.565***	0.550***	0.739***
	(0.020)	(0.024)	(0.027)	(0.027)
Output measure	Patent valuations	Δ Revenue	Δ Employment	Δ Labor Productivity
1-Year AR(1)	0.93	0.89	0.89	0.94
R2-Within	0.46	0.30	0.28	0.59
Observations	7,623	7,455	6,447	7,411

Note: Table reports 5-year autocorrelation coefficients. Regressions control for NAICS3× Year effects. Standard error clustered at the NAICS6 level.

Standard errors in parentheses. Significance levels: * 10% , ** 5%, *** 1%.

Second, most of the variation in R&D returns is within narrow industries. As reported in Table 2, the standard deviation of R&D returns only decreases by 15% when focusing on variation within NAICS6×industry cells. Furthermore, it remains more than 40% larger than the respective dispersion in the return on capital. Differences in R&D returns thus persist even when comparing arguably highly comparable firms operating at the same point in time and in the same industry.

Table 2: Return Dispersion Across Comparison Groups

Within Cell	Return on R&D	Return on Capital	
	SD	SD	Δ%
—	1.11	0.77	43.4%
Year	1.06	0.74	44.2%
NAICS3 × Year	0.93	0.64	46.4%
NAICS6 × Year	0.84	0.58	45.7%

Note: Return measures residualized with respect to fixed effects indicated in first column. Column headers SD report standard deviations of return measure. Columns headers Δ% indicate percent difference of Return on R&D dispersion with respect to return in consideration. Returns are measured in logs.

3.4 R&D Returns in Theory

While R&D returns are widely dispersed empirically, workhorse endogenous growth models predict expected R&D return equalization in absence of frictions (Romer, 1990; Aghion and Howitt, 1992; Acemoglu and Cao, 2015). Firms with above equilibrium returns expand their R&D activity and thereby, due to diminishing returns, transition back to the equilibrium return and vice versa. In this section I will derive this result formally and show that we can think about R&D through the lens of frictions or market imperfections. I will focus on a setup with inventors in the R&D productions function here, but equivalent results can be derived for a lab-equipment model.[16]

Let ℓ be the number of inventors hired by the firm at unit cost W, which the firm takes as given. Inventors create R&D output $z(\ell)$, which the firm values at price V, with a decreasing returns to scale production function with scale elasticity γ and R&D productivity φ. The firm's optimization problem is thus given by

$$\ell^* = \arg\max_{\ell} \{z(\ell) \cdot V - \ell \cdot W\} \quad \text{s.t.} \quad z = \varphi \cdot \ell^{\gamma}. \tag{3}$$

The first order conditions of this problem imply that the equilibrium R&D return, i.e. the benefits of R&D divided by the cost, is a function of the scale elasticity only:

$$\text{Expected R\&D Return} \equiv \frac{z(\ell^*) \cdot V}{\ell^* \cdot W} = \frac{1}{\gamma}. \tag{4}$$

Importantly, workhorse models assume that γ is a constant, as in this example, and that it is common across firms.[17] Thus, workhorse model predict no dispersion in R&D returns.[18]

One potential source of R&D return dispersion suggested by this formulation is differences in the scale elasticity γ across firms, however, as shown above, most of the variation in returns is within narrow industries, where we might expect technology to be reasonably similar. The question thus becomes how we can think about R&D return dispersion in practice. I will discuss two potential mechanisms here: frictions and input market imperfections.

[16]The lab equipment setup effectively assumes a cost function $C(z)$ instead of a production function. Setting $C(z) = (1/\varphi) \cdot z^{(1/\gamma)}$ reproduces the results in the model below. See e.g. Gancia and Zilibotti (2005).

[17]See e.g. Acemoglu and Cao (2015); Acemoglu et al. (2018); Akcigit and Kerr (2018b); de Ridder (2021) for recent examples.

[18]Note that this insight is unaffected by heterogeneity in the value of R&D V, R&D efficiency φ, and input price W. In fact, firms with larger value of innovation, higher efficiency, and lower input prices conduct more R&D, however, R&D output and cost scale proportionally such that their ratio is constant.

Consider the case of frictions first and assume that the firm's first order conditions are subject to exogenous wedge Δ, which is due to constraints imposed by frictions:

$$\frac{\partial z(\ell)}{\partial \ell}\bigg|_{\ell=\ell^*} \cdot V = W \cdot (1+\Delta), \tag{5}$$

where $\Delta = 0$ recovers the unconstrained case. R&D returns are then given by

$$\text{Expected R\&D Return} \equiv \frac{z(\ell^*) \cdot V}{\ell^* \cdot W} = \frac{1}{\gamma} \cdot (1+\Delta). \tag{6}$$

It follows immediately that variation in Δ will lead to variation in the expected R&D return as well. Severely constrained firms, i.e. those with large Δ, have large R&D returns and vice versa. The intuition for this results is that constrained firms conduct less R&D than they would like and, thus, forgo some lower value projects at the margin, which gives them larger average R&D returns. Dispersion in R&D returns then becomes a sign that firms are differentially constrained in their R&D input choice, which could lead to misallocation.

In companion paper Lehr (2022) I build on this result in an endogenous growth model with fixed inventor supply. Under these assumptions, the growth rate is the product of the frontier growth rate, achievable by the growth-maximizing allocation, and an allocative efficiency adjustment term.[19] The latter is determined by frictions Δ and declines in their dispersion. Under the assumption that R&D return dispersion is due to frictions only, I estimate an allocative efficiency of around 70% implying a frontier growth rate $1/0.70 - 1 \approx 40\%$ larger than the realized growth rate. The estimate thus suggests that the potential growth impact associated with the measured R&D return dispersion is large.

Consider the case of input market imperfections next and assume that the firm's wage depends on its inventor workforce with local inverse labor supply elasticity $\epsilon(\ell^*) = \frac{\partial \ln W(\ell)}{\partial \ln \ell}\big|_{\ell=\ell^*}$, where $\epsilon(\ell^*) = 0$ for price takers. Then, equilibrium R&D returns are given by

$$\text{Expected R\&D Return} \equiv \frac{z(\ell^*) \cdot V}{\ell^* \cdot W} = \frac{1}{\gamma} \cdot (1+\epsilon(\ell^*)), \tag{7}$$

Firms with significant monopsony power have higher R&D returns. The intuition is similar to frictions as firms with market power reduce their hiring of inventors at the margin to keep wages low and, thus, also forgo some marginal R&D projects, which raises the average value of the conducted projects and therefore R&D returns. Through this lens, R&D returns

[19] See Appendix D for a full exposition and derivation of the main result.

might reflect differences in the inverse labor supply elasticity faced by firms at the margin. For example, if firms hiring more inventors have more pricing power, i.e. larger $\varepsilon(\ell^*)$, then theory would predict that they have higher returns as well. Similarly, there might be more pricing power for firms operating in highly specialized markets or when workers have strong preferences over firms (Manning, 2003; Card et al., 2018). With market power in the input markets, R&D returns reflect markdowns and their heterogeneity.

Both channels for R&D return dispersion discussed in this section, frictions and monopsony power, suggests that it might be associated with less than optimal allocation of R&D resources from a planners perspective., however, note that expected R&D return equalization is not necessarily efficient from a growth perspective. Planner and firm incentives differ in endogenous growth models due to the intertemporal externality of knowledge creation (Romer, 1990; Aghion and Howitt, 1992). Building on this insight, the recent literature highlights that resource allocation across firms might be inefficient due to heterogeneous gaps between planner and private valuation of innovation (Acemoglu et al., 2018; de Ridder, 2021; Aghion et al., 2022a). This insight is distinct to my results on R&D return dispersion, which is concerned with the optimal allocation of R&D resources from a private perspective. Note also that the private R&D return is equalized across firms in the before mentioned papers, which is at odds with my findings.

4 Inventor Markets and R&D Dispersion

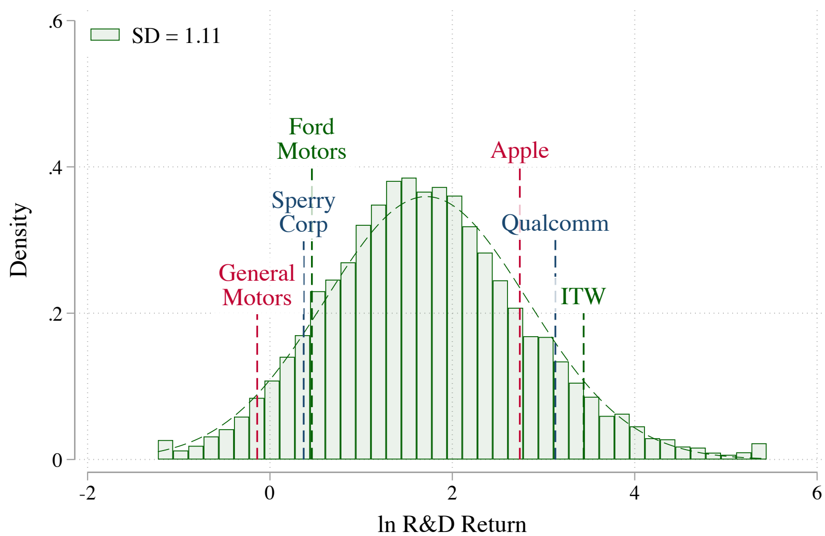
The previous section established that R&D returns are highly dispersed empirically, which is at odds with the prediction of benchmark endogenous growth models. Furthermore, I showed that we can interpret R&D return dispersion as a potential sign of frictions or imperfections in the market for inventors. I present some evidence on the potential importance of frictions in Appendix B.3, where I show that R&D returns are uncorrelated with conventional measures of financial frictions and subsidies . Here, I focus on inventor market imperfections instead, motivated by two observations. First, R&D is mostly a “people business” driven by inventors and scientists such that labor accounts for c. 80% of directly attributable R&D cost according to the 2019 NSF Business Enterprise Research and Development Tables.[20] And, second, R&D returns are systematically larger for firms with high innovative capacity.

[20]I calculate total attributable R&D cost as the sum of expenditure on labor, materials, depreciation, and cost of capital. I impute the cost of capital as 1/3 of depreciation, which is in line with a 15% depreciation rate and a 5% cost of capital.

4.1 R&D Returns for Innovative Firms

Highly innovative firms tend to earn larger R&D returns. Figure 2 reports the histogram of R&D returns together with long-run average returns for selected firms. Firms that are often identified as particularly innovative such as Apple and Qualcomm tend to have above average R&D returns, while firms that are less known for innovation, at least within the time-frame covered by my sample, such as Ford and General Motors tend to have lower returns. Indeed, as reported in Appendix E, many known tech companies rank in the top 50 of long-run R&D returns, while the bottom 50 is dominated by less innovative firms.

Figure 2: Returns on R&D are Highly Dispersed



Notes: Histogram of log expected R&D returns. Firms are plotted at their long-run average returns. SD refers to the standard deviation. See Section 2 and Appendix A for data detail.

Corroborating this finding more systematically, Table 3 reports a strong correlation of R&D returns with measures of inventor employment, which accounts for a significant share of the variation in R&D returns. Column (1) reports that variation in the number of inventors can account for 7% of the variation R&D returns. Adjusting for inventor quality further increases the explanatory power to above 10%, regardless of whether I simply use the long-run average R&D output of inventors as in column (2) or whether I adjust this output for firm effects as in column (3).[21] Furthermore, these association are not due to overall firm size. Column (4) confirms that total employment has quantitatively and statistically insignificant association with R&D returns controlling for effective inventor employment.

[21] See Appendix A for details on the quality adjustment.

Table 3: R&D Returns and Inventor Employment

	(1)	(2)	(3)	(4)
		R&D Return		
Inventors	0.228***			
	(0.032)			
Inventors (Quality-adjusted)		0.289***	0.253***	0.263***
		(0.022)	(0.031)	(0.033)
Total Employment				-0.018
				(0.026)
Quality adjustment	—	Long-run	AKM	AKM
R2-Within	0.07	0.23	0.15	0.15
Observations	11,845	11,845	11,844	11,812

Note: This table reports OLS coefficient estimates. Columns (2)-(5) adjust inventor employment for quality. I measure inventor quality either using annual value creation attributable to the inventor, which I average over the inventor's career. AKM values residualize inventor quality with respect to firm fixed effects. All variables are measured in logs. Standard errors are clustered at the NAICS6 level.

Standard errors in parentheses. Significance levels: * 10% , ** 5%, *** 1%.

One potential interpretation of this finding along the mechanisms discussed in the previous section is that firms employing more inventors might have more monopsony power. According to this interpretation, the positive correlation between R&D returns and inventor employment arises because $\epsilon(\ell^*)$ is increasing in ℓ^*. I will explore this possibility next.

4.2 Estimating Inventor Monopsony

A large literature argues that monopsony power is pervasive in the labor market and quantitatively important for the allocation of workers in the production sector.[22] The literature also finds that high-skilled workers, a group likely including many inventors and research scientists, are more affected by monopsony.[23] Furthermore, there is mounting evidence that especially large tech firms are aware of their market power and attempt to exploit it.[24]

[22]See e.g. Manning (2011); Card et al. (2018); Kroft et al. (2021); Manning (2021); Sokolova and Sorensen (2021); Berger et al. (2022); Lamadon et al. (2022); Schubert et al. (2022); Yeh et al. (2022)

[23]See Prager and Schmitt (2021); Seegmiller (2021); Friedrich et al. (2021)

[24]For example, it is well known that large Tech firms had agreements between each other not to poach employees in order to keep wages low. Apple, Adobe, Intel, and Google got fined by the Department of Justice in 2010 for illegal non-poaching agreements to keep salaries for tech workers low with further

As discussed in the previous section, monopsony power is reflected in R&D returns as firms exploiting it reduce their inventor employment to keep wages low and, thus, have to scale back on R&D, which gives them larger average returns due to diminishing returns to scale. The extend of this force depends on the firm-specific labor supply elasticity such that firms facing inelastic supply scale back more and, therefore, earn higher returns. Heterogeneity in the firm-specific inventor supply elasticity can thus lead to dispersion in R&D returns. This mechanism can also account for the link between R&D returns and inventor employment if monopsony power increases with the latter. Indeed, the existing literature suggests just that for the general labor market (Berger et al., 2022; Yeh et al., 2022).

It, thus, would not be surprising to find monopsony in the inventor market nor that it can explain the link between R&D returns and inventor employment, however, there is no direct evidence thereof for inventors yet. In the following, I fill this gap by estimating that the inventor supply elasticity is indeed smaller for firms with high R&D returns and firms with large inventor employment. For this purpose, I first discuss estimation of the inverse supply elasticity first, before linking it to R&D returns and inventor employment.

One approach to estimating the inverse labor supply elasticity is to regress log changes in the inventor wage on changes in log inventor employment as shown in equation (8). The coefficient on the changes in inventor employment identifies the average inverse labor supply elasticity if the error term is uncorrelated with changes in inventor employment.

$$\Delta \ln \text{Inventor Wage}_{it} = \bar{\epsilon} \times \Delta \ln \text{Inventors}_{it} + \alpha_{j(i)\times t} + \varepsilon_{it} \tag{8}$$

A natural challenge in this regression are labor supply shocks that simultaneously affect wages and employment. For example, if a firm becomes more attractive to employees for independent reasons, we might expect that the firm will be able to lower wages and higher more workers, however, this variation does not answer the questions as to what happens to wages if the firm wants to expand employment. In other words, supply shocks confound the estimation of a supply elasticity, and we thus need demand shocks for identification.

Following Seegmiller (2021), I propose to use stock market returns as an instrument for inventor employment. The idea behind the instrument is that stock market returns reflect changes in firm productivity or demand for a firm's product that incentivize it to expand.

subsequent investigations. See here, here, here. Microsoft only recently announced that it will not enforce its non-compete clauses for employees and was previously sued for their non-poaching agreements. Similar cases have emerged in other industries.

Seegmiller (2021) uses the instrument for employment in general, but the argument extends to innovators. The identification assumption is thus that stock market returns do not affect changes in inventor wages other than through their impact on the demand for inventors.

I connect the inverse labor supply elasticity with R&D returns by adding an interaction term for firms with above median R&D return to the regression framework. If R&D return dispersion is partly driven by heterogeneity in the firm-specific labor supply elasticity, then we would expect a positive coefficient on the interaction term as firms with high R&D returns face a high inverse labor supply elasticity. I follow a similar approach for above and below median inventor employment.

$$\begin{aligned}\Delta \ln \text{Inv. Wage}_{it} = \quad & \epsilon_l \times \Delta \ln \text{Inv.}_{it} \\ & + (\epsilon_h - \epsilon_l) \times \Delta \ln \text{Inv.}_{it} \times \{\text{Above Median Return on R\&D}\}_{it} \\ & + \beta\{\text{Above Median Return on R\&D}\}_{it} + \alpha_{j(i)\times t} + \varepsilon_{it}\end{aligned} \tag{9}$$

I measure inventor wages as the ratio of R&D spending to inventors at the 5-year level, which motivated by the high labor share in innovative discussed above. In the context of my regression, this is a valid proxy for true inventor wages unless changes in the labor intensity of R&D or share of R&D workers identified by patents are correlated with stock market returns. Using 5-year windows allows me to pick up medium run effects. Note, however, that the instrument only captures annual variation, which safeguards the estimated coefficient from concerns around the use of long-run averages.

My estimation results, as reported in Table 4, reveal three novel findings: first, estimated inverse labor supply elasticities are significantly different from 0 such that expanding firms face higher wages. A 1% increase in employment is associated with a 0.96% increase in average wages. The effect size is of comparable magnitude to the estimate of 0.84 for high-skilled workers in Seegmiller (2021), who uses detailed LEHD data on wages and employment. Second, these effects are stronger for firms with high R&D returns. A firm with above median R&D return faces an inverse labor supply elasticity of $0.817 + 1.079 \approx 1.9$ implying that a 1% increase in employment requires a 1.9% increase in wages. Translating the differences in the labor supply elasticity into markdowns, I find they can account for around 30% of the average difference in R&D returns between above and below median R&D return firms.[25] Third, column (3) reveals that the inverse labor supply elasticity is

[25] The ratio of average R&D returns above and below the median is 5.7, while the ratio of implied markdowns is $(1 + 1.079 + 0.817)/(1 + 0.817) \approx 1.6$. The ratio of both is $1.6/5.7 \approx 30\%$.

indeed larger for firms with high inventor employment, which suggests that the correlation of employment and R&D returns is indeed partly driven by markdowns. Differences in the labor supply elasticity explain approximately the entire difference between R&D returns of above and below median inventor employment firms.[26]

Table 4: Inventor Inverse Labor Elasticity Estimates

	(1)	(2)	(3)
	$\Delta \ln$ `Inventor Wage`$_{it}$		
$\Delta \ln$ `Inventors`	0.963***	0.817**	0.410**
	(0.198)	(0.325)	(0.203)
— × {Top 50% R&D Return}		1.079**	
		(0.512)	
— × {Top 50% Inventors}			1.245***
			(0.446)
{Top 50% R&D Return}		-0.224***	
		(0.044)	
{Top 50% Inventors}			-0.090***
			(0.020)
First stage F stat. (Main)	96	39	48
First stage F stat. (Inter.)		60	71
Observations	14,834	14,834	14,834

Note: This reports the second stage results for the main specification. All regressions control for NAICS3 × year fixed effects. Standard errors clustered at the NAICS6 level.

Standard errors in parentheses. Significance levels: * 10% , ** 5%, *** 1%.

I report the first stage results in Appendix B.4. The coefficient have the expected sign and the first stage F-statistic indicates a comfortably high level of power for my instruments. I also report regressions controlling for changing inventor productivity and lagged changes in wages and employment. Changes in inventor productivity correlate with wages growth, but the main regression coefficient remain unaffected. Controlling for lagged changes in employment and wage as in Seegmiller (2021) increases the estimated coefficients significantly.

[26]The ratio of average R&D returns for firms with above and below inventor employment is 1.8, while the ratio of implied markdowns is $(1 + 1.245 + 0.410)/(1 + 0.410) \approx 1.9$.

5 Monopsony, R&D Return Dispersion, and Growth

I quantify the potential importance of heterogeneous inventor labor supply elasticities for R&D return dispersion and economic growth in a Schumpeterian endogenous growth model with heterogeneous firms. Firms differ in their R&D productivity and labor supply elasticity. I parametrize the model using a combination of external calibration and moment matching.

5.1 Model Description

Time is discrete, infinite and indexed by $t = 0, ..., \infty$. At any point in time there is a constant mass of firms normalized to 1.

Households. The representative household has logarithmic preferences over per-capita consumption c_t and discounts the future with discount factor β. The household consists of a unit mass of workers, whereof a share L are inventors and the remainder production workers. Inventors have labor disutility $u(\{\ell_{it}\})$ depending on their distribution over firms and earn firm-specific wages W_{it}, while production workers have no labor disutility and earn $\tilde{W}_t$. The household owns all firms and their profits Π_t. Finally, there is a riskless bond B_t available in zero net-supply paying interest R_t. The household's problem is given by

$$\begin{aligned}
&\max \sum_{t=0}^{\infty} \beta \left(\ln c_t - u(\{\ell_{it}\})\right) \\
&\text{s.t.} \quad C_t = R_t B_t - B_{t+1} + \int_0^1 \ell_{it} W_{it} di + (1-L)\tilde{W}_t + \Pi_t \\
&\text{and} \quad \int_0^1 \ell_{it} di \leq L.
\end{aligned} \tag{10}$$

I define the labor disutility function implicitly by assuming a labor supply in the spirit of Card et al. (2018) and Kline et al. (2019):

$$\frac{\ell_{it}}{L} = \left(\frac{W_{it}}{W_t} - \bar{\ell}\right)^{\frac{1}{\xi}} \tag{11}$$

The term W_t is a common wage-shifter determined by labor market clearing. The parameter ξ governs the average labor supply elasticity such that we recover the case with common wages and fully elastic supply by setting $\xi = 0$. Intercept parameter $\bar{\ell}$ and "relative wage" $\frac{W_{it}}{W_t}$ determine labor supply across firms. Importantly, this formulation delivers a non-homothetic labor supply elasticity if $\bar{\ell} > 0$, which will be essential to creating dispersion in R&D returns.

In Card et al. (2018), ξ is linked to the relative importance of non-monetary compensation and $\bar{\ell}$ to workers' outside option. I discuss the micro-foundation in Appendix C.2.

The standard Euler equation requires

$$\frac{c_{t+1}}{c_t} = \beta R_{t+1}. \tag{12}$$

Static production. Aggregate output Y_t is produced from product-line output y_{jt} with Cobb-Douglas production function. Product-line output is the aggregate across firm production of the particular product, where output across firms are perfect substitutes.

$$\ln Y_t = \int_0^1 \ln(y_{jt})dj \qquad \text{with} \qquad y_{jt} = \int_0^1 y_{ijt}di. \tag{13}$$

Each firm has a productivity portfolio $\mathcal{A}_{jt} = \{A_{ijt}\}_{j\in[0,1]}$ and produces with linear technology in production labor l_{ijt}:

$$y_{ijt} = A_{ijt}l_{ijt}. \tag{14}$$

Production labor is hired at production wage $\tilde{W}_t$ and firms compete in Bertrand competition in the product market. Let $A_{jt} = \max_i\{\{A_{ijt}\}_{i\in[0,1]}\}$ be the highest productivity in a product line, $\bar{A}_{jt} = \max_i\{\{A_{ijt}\}_{i\in[0,1]} \setminus \{A_{jt}\}\}$ the second highest, and the leader's productivity advantage $\lambda_{jt} = A_{jt}/\bar{A}_{jt}$ their ratio. In the limit pricing equilibrium, firms with productivity $\bar{A}_{jt}$ are the sole producer in a product line, while charging the marginal cost of second best firm. The equilibrium yields maximal profits for the best firms without giving competitors an incentive to produce. Equilibrium profits π_{jt}, labor demand l_{jt}, and output y_{jt} are

$$\pi_{jt} = Y_t \cdot (1 - 1/\lambda_{jt}), \qquad l_{jt} = \frac{1}{\lambda_{jt}}\frac{Y_t}{\tilde{W}_t} \qquad \text{and} \qquad y_{jt} = A_{jt}l_{jt}. \tag{15}$$

The production wage $\tilde{W}_t$ is pinned down by market clearning:

$$1 - L = \int_0^1 \int_0^1 l_{ijt}djdi. \tag{16}$$

As shown in Peters (2020), this setup gives rise to a simple aggregate production function depending on aggregate productivity index A_t, a production efficiency term Λ_t depending on the distribution of $\{\lambda_{jt}\}$, and the mass of production workers $1 - L$:

$$Y_t = A_t \Lambda_t (1 - L) \quad \text{with} \quad \ln A_t = \int_0^1 \ln(A_{jt}) dj \quad \text{and} \quad \Lambda_t = \frac{\exp\left(\int_0^1 \ln\left(\frac{1}{\lambda_{jt}}\right) dj\right)}{\int_0^1 \left(\frac{1}{\lambda_{jt}}\right) dj}. \tag{17}$$

Innovation. Firms innovate to become leaders in new product lines. In turns, they lose their status as a leader whenever a competitor innovates in one of their product lines. Firms innovate with probability z_{it} depending on their R&D efficiency φ_{it} and hired inventors ℓ_{it}:

$$z_{it} = e^{\mu + \varphi_{it}} \ell_{it}^{\gamma}, \tag{18}$$

where μ governs the common R&D productivity. When a firm successfully innovates, it becomes the leader in a random new product line and draws associated productivity advantage $\lambda \sim f_{\lambda}$. I assume that the distribution over potential productivity advantages is common across firms and constant over time.

The firm's idiosyncratic R&D efficiency follows an AR(1) process:

$$\varphi_{it} = \rho \varphi_{it-1} + \nu_{it} \qquad \text{with} \qquad \nu_{it} \overset{i.i.d.}{\sim} N(0, \sigma_{\varphi}^2). \tag{19}$$

Firms face R&D cost $C(\ell_{it}, \ell_{it-1})$, which features heterogeneous, finite labor supply elasticities via a firm specific innovator wage W_{it} as well as adjustment cost AC_{it}:

$$C_t(\ell_{it}, \ell_{it-1}) = W_{it} \ell_{it} (1 + AC_{it}). \tag{20}$$

The labor supply formulation gives rise to the firm specific innovator wages with finite and heterogeneous labor supply elasticity, which firms take into account:

$$W_{it} = W_t \left((\ell_{it})^{\xi} + \bar{\ell} \right). \tag{21}$$

I allow for quadratic adjustment cost to allow for dynamic frictions in the labor market:

$$AC_{it} = \phi \left(\frac{\ell_{it} - (1 - \delta) \ell_{it-1}}{\ell_{it-1}} \right)^2. \tag{22}$$

Here, ϕ captures the strength of adjustment cost and δ natural employment turnover.

With slight abuse of notation, I will denote a firms productivity advantage portfolio by $\mathcal{A}_{it} = \{\lambda_{jt}\}_{j \in \mathcal{J}_{it}}$, where $\mathcal{J}_{it}$ is the set of product lines in which firm i is the leader at time t. Note that this set could be empty. Then, the firm's dynamic problem is given by

$$V_t(\mathcal{A}_{it}, \varphi_{it}, \ell_{it-1}) = \max_{\ell_{it}} \Big\{ \sum_{j \in \mathcal{J}_{it}} \pi_{jt} - C_t(\ell_{it-1}, \ell_{it}) + \left(\frac{1}{R_t}\right) \mathbb{E}_t \big[V_{t+1}(\mathcal{A}_{it+1}, \varphi_{it+1}, \ell_{it}) \big] \Big\}. \quad (23)$$

Expectations are taken with respect to the R&D efficiency process, a potential realization of λ, and the evolution of the existing product lines in $\mathcal{A}_{it}$. For each $j \in \mathcal{J}_{it}$, the firm remains the leader with probability $1 - z_t$ and loses its leader status otherwise, where z_t is the aggregate innovation rate:

$$z_t = \int_0^1 z_{it} di. \quad (24)$$

Thus, for $\lambda_{jt} \in \mathcal{A}_{it}$, $\lambda_{jt} \in \mathcal{A}_{it+1}$ with probability $1 - z_t$. Furthermore, with probability z_{it} a λ drawn from distribution f_λ becomes part of $\mathcal{A}_{it+1}$.

The common wage-shifter W_t is determined by labor market clearing for inventors:

$$L = \int_0^1 \ell_{it} di. \quad (25)$$

Definition 1. *A competitive equilibrium is a sequence of prices $\{W_t, R_t\}$, quantities $\{\ell_{it}, Y_t, A_t, \Lambda_t\}$, productivity portfolios $\{\mathcal{A}_{it}\}$ and efficiency distributions $\{\varphi_{it}\}$, and value function $\{V_t(\mathcal{A}_{it}, \varphi_{it}, \ell_{it-1})\}$ such that firms optimize, markets clear, and the above defined laws of motion are satisfied.*

5.2 Characterizing the Equilibrium

I analyze, calibrate, and simulate the model in recursive formulation along a balanced growth path, which is summarized in Definition 2. Two properties are useful in deriving the recursive form. First, the model formulation allows me to decompose the value function into a profit and R&D component. The former captures the expected net-present-value of the profits associated with existing leadership positions and is independent of a firm's R&D choices. The latter captures the value of the firm's ability to conduct R&D and create leadership positions in the future. Second, as in other endogenous growth models, the growth-rate in this economy is the expected productivity improvement of an invention times the aggregate innovation rate. The latter crucially depends on the allocation of inventors and is the direct vehicle through which frictions impact growth. See Appendix C.1 for details.

Definition 2. *A recursive Balanced Growth Path equilibrium is a growth rate g, prices*

$\{W, R, \mathcal{V}(\lambda)\}$, *value function* $\tilde{V}(\varphi, \ell)$ *with policy function* $\ell'(\varphi, \ell)$, *distribution* f_λ, f_φ *and* $f(\varphi, \ell)$ *such that*

- *the value function and policy function solve*

$$\begin{aligned} V(\ell, \varphi) &= \max_{\ell'} \{-C(\ell, \ell') + \beta \left(z(\varphi, \ell')\mathbb{E}_\lambda[\mathcal{V}(\lambda)] + \mathbb{E}[V(\ell', \varphi')]\right)\} \\ s.t. \quad C(\ell, \ell') &= W\ell' \left(\ell' + \bar{\ell}\right)^\xi \left(1 + \phi \left(\frac{\ell'}{\ell} - (1-\delta)\right)^2\right) \\ \mathbb{E}_\lambda[\mathcal{V}] &= \frac{1 - \mathbb{E}_\lambda[1/\lambda]}{1 - \beta(1-z)} \quad \textit{and} \quad z(\varphi, \ell') = e^{\mu+\varphi} \cdot \ell'^\gamma. \end{aligned} \tag{26}$$

- *the aggregate innovation and growth rate are given by*

$$g = z \cdot \mathbb{E}_\lambda[\ln \lambda] \quad \textit{and} \quad z = \int \left(e^{\mu+\varphi} \cdot \ell'(\varphi, \ell)^\gamma\right) dF(\varphi, \ell) \tag{27}$$

- *labor market clearing holds*

$$\mathcal{L} = \int \ell'(\varphi, \ell) dF(\varphi, \ell) \tag{28}$$

- *the distribution function* $f(\varphi, \ell)$ *satisfies*

$$f(\varphi', \ell') = \int f(\varphi, \ell)\{\ell'(\varphi, \ell) = \ell'\} f_\varphi(\varphi'|\varphi) dF(\varphi, \ell), \tag{29}$$

where $f_\varphi(\varphi'|\varphi)$ *is the conditional density over* φ'.

The model generates dispersion in the return on R&D through two channels: Non-homothetic wages ($\bar{\ell} > 0$) and adjustment cost ($\phi > 0$). Adjustment cost lead to dispersion as firms adjust their R&D expenditure gradually in response to a R&D productivity shocks, while R&D output responds immediately. Thus, firms receiving a positive productivity shock have temporarily elevated R&D returns and vice versa.

Lemma 1. *Suppose* $\gamma = 0$, *then the expected return on R&D is given by*

$$\frac{z(\varphi, \ell^*(\varphi))\mathbb{E}_\lambda[\mathcal{V}(\lambda)]}{C(\ell^*(\varphi))} = \frac{1}{\gamma} \cdot \left(1 + \xi \cdot \frac{(\ell^*(\varphi))^\xi}{(\ell^*(\varphi))^\xi + \bar{\ell}}\right). \tag{30}$$

Non-homothetic wages, as summarized in Lemma 1, yield dispersion in R&D returns due to local differences in the labor supply elasticity. Firms with large inventor employment face less elastic supply and thus have stronger incentives to suppress their inventor demand in order to reduce their wages. The formulation thus connects the labor supply elasticity with labor demand and, in equilibrium, with R&D productivity. It is thus exactly in line with documented correlation of R&D returns and employment as well as the labor supply elasticity estimates in Table 4.[27]

5.3 Numerical Solution and Simulation

I solve the model numerically using discretization methods. I create a large grid for labor input choices and discretize the productivity process using the Tauchen method. I then solve the firm's problem via value function iteration and employ non-stochastic simulation to calculate aggregates for market clearing. My baseline algorithm enforces a growth rate of 1.5% p.a. via the average R&D efficiency parameter μ. See Appendix C.3 for further details.

I calculate model moments by simulating a single firms for 100,000 periods with an additional 50 "burn-in" periods at the beginning. I assume that the firm has N_P different R&D lines with perfectly correlated R&D productivity process. R&D success and patent valuation are independent across product lines making the number of patents per period a Bernoulli random variable. I add ex-ante uncertainty in patent valuations and, thus, ex-post measurement error in R&D returns by drawing them from a geometric distribution:[28]

$$\lambda_{it} = \lambda^{\Delta_{it}} \quad \text{with} \quad Pr(\Delta_{it}) = (1-P)P^{\Delta-1} \quad \text{for} \quad \Delta = 1, 2, ... \tag{31}$$

Using the simulated data I construct the relevant sample moments. Throughout, I perform the same operations on the simulated data as for deriving my empirical estimates.

5.4 Calibration

I parameterize the model with a combination of external calibration and moment matching.

External calibration. Firstly, I set the discount factor β to 0.97, which, together with a targeted growth rate of 1.5%, implies an annual interest rate of c. 4.5% and is broadly in line with standard calibrations (Acemoglu et al., 2018). Secondly, I set the R&D scale elasticity ϕ to 1 (Acemoglu et al., 2018). The elasticity controls firms' sensitivity to R&D productivity shocks. Finally, I calibrate the depreciation rate for R&D workers δ to 12.5%, which matches

[27]It is also in line with the evidence presented in Seegmiller (2021) and Yeh et al. (2022). Note that the monopsony model in Berger et al. (2022) also has the feature that larger firms face less elastic labor supply.

[28]Note that the firm is risk-neutral and only takes the expected value of profits $\mathbb{E}[\pi(\lambda_{it})]$ into consideration.

the natural turnover of employees in the LED Quarterly Workforce Indicators.[29] Higher levels of δ lead to an asymmetry in adjustment cost, making it costlier to grow than to shrink.

Internal calibration/ moment matching. I split the internal calibration into two steps. Firstly, I calibrate the parameters for the patent valuation process, λ and P, to match an average markup of 20% together with the within firm-year standard deviation of log patent valuations in my sample. The step-size parameter λ primarily controls the average markup, while P is closely linked to the dispersion of patent valuation. I can perform this step separately as both moments only depend on the process for λ_{it}. Imposing a relatively large λ via a large average markup ensures that the probability of invention z remains well below 1. Note that conditional on a targeted growth rate, the size of λ does not influence the aggregate as larger values simply imply lower required levels of average R&D efficiency.

After this step, five parameters remain to calibrate: the standard deviation σ and auto-correlation ρ of the R&D efficiency process, the parameters of the wage function, ξ and $\bar{\ell}$, and adjustment cost γ. I calibrate them by targeting the 8 moments listed in Table 5, which concern the behavior of R&D expenditure and inventor employment, estimated wage elasticities, and auto-correlations of R&D returns. I match moments by minimizing the weighted distance of model and data moments using absolute differences in percent except for the auto-correlation for R&D growth, where I use level differences. Moments are weighted to emphasize the basic behavior of R&D expenditure together with my estimates from the previous section. The targeted moments and parameters are intimately linked in the model, however, some relationships are particularly important for identification. Firstly, the standard deviation of R&D growth is positively linked to the dispersion in R&D productivity shocks. Secondly, the auto-correlation of R&D productivity and adjustment costs both increase the auto-correlation of log R&D and its changes, however, with different sensitivities. Finally, the wage elasticity estimates are linked to the wage function, where the average elasticity is primarily governed by ξ, while the relative elasticities allow us to identify $\bar{\ell}$ by governing the dispersion in R&D returns. More heterogeneity generally requires larger $\bar{\ell}$.

Table 5 reports the targeted moments together with their model counterparts and confirms a good fit overall except for the final two moments. Note that the model delivers auto-correlated R&D returns, however, it does not quite capture the magnitude. Auto-correlation

[29] In the data, I first calculate the turnover of employees that is not linked to net-flows as gross minus net worker turnover, which captures workers turnover within industries, and then normalize this number by employment and take a simple average to get an aggregate estimate of 12.5%.

arises due to combination of the wage function and auto-correlated R&D productivity. In particular, the wage function links the inverse labor supply elasticity, and thus R&D returns, to the labor demand. The latter is positively auto-correlated due to the productivity process, making the return on R&D auto-correlated as well.

Table 5: Model vs Data Moments

Moment	Data	Model	Target	Source
Average markup	0.200	0.200	λ	Norm.
SD of log patent valuations	0.562	0.562	P	Data
SD of R&D growth	0.316	0.316	σ	Data
Auto-corr. of log R&D	0.922	0.922	ρ	Data
Auto-corr. of R&D growth	-0.017	0.028	γ	Data
Avg. wage elasticity	0.923	0.986	$\{\xi, \bar{\ell}\}$	Data
Avg. wage elas. for low R&D returns	0.756	0.672	ξ	Data
Diff. in avg. wage elas. high vs low R&D returns	1.119	1.089	$\bar{\ell}$	Data
Inventor - R&D expenditure elas.	0.638	0.517	$\{\xi, \bar{\ell}\}$	Data
Auto-corr. of Return on R&D	0.651	0.437	$\{\xi, \bar{\ell}, \gamma\}$	Data

Note: This table reports model and data moments targeted in the calibration the model with monopsony power. Model values based on simulation with 100,000 observations. I estimate the auto-correlations accounting for permanent firm differences as in Han and Phillips (2010). The estimated wage elasticities respond to the estimates in columns (1) and (2) of Table 4. The return on inventors is defined as the ratio of patent valuations to inventors. The final two auto-correlations are calculated at the 5-year horizon.

Table 6 reports the calibrated parameters. R&D productivity is highly auto-correlated and its innovations are highly volatile.[30] The large calibrated volatility is mainly due to the presence of monopsony power, which reduces R&D expenditure volatility by increasing the concavity of the firm's objective function. The calibrated adjustment cost are small and imply that a firm increasing its employment by 10% faces an additional cost of 0.4% of its wage bill.[31] Finally, the calibration for labor supply implies a highly convex wage and labor supply elasticity in inventor employment. Firms hiring few inventors effectively face a competitive inventor market, while firms with large inventor workforce have significant pricing power. This difference has large effects on wages. Firms at the upper end of the employment distribution pay workers around 3 times as much as low R&D employment firms.

[30]For example, the volatility of profitability shocks, which directly map into R&D productivity, in Terry (2022) is about one fourth of my parameter estimate, while the auto-correlation is of comparable magnitude.

[31]Cooper and Haltiwanger (2006) estimate an adjustment cost parameter of 0.455 for capital investment, while Asker et al. (2014) estimate a value above 8.

Table 6: Calibrated Parameters

Parameter	Description	Value	Source
A. External calibration			
β	Discount factor	0.970	Standard value
γ	R&D scale elasticity	0.500	Acemoglu et al. (2018)
L	Researchers	0.142	Acemoglu et al. (2018)
δ	Inventor turnover	0.120	Natural turnover in LED
B. Internal calibration			
λ	Minimum step size	1.080	Direct
$\bar{P}$	Step size shape parameter	0.447	Direct
σ	Std. dev. R&D prod. shocks	0.446	Moment matching
ρ	Autocorr. R&D prod.	0.867	Moment matching
γ	Adjustment cost	0.101	Moment matching
ξ	Avg. inventor elasticity	4.755	Moment matching
$\bar{\ell}$	Rel. inventor elasticity	3.884	Moment matching

Note: Table reports model calibration.

Data- vs model-implied returns. The model links R&D returns to inventor employment via the wage elasticity. I test this link empirically by estimating the log-transformed expression in Lemma 1 via OLS, constructing the model-implied wage elasticity by combining the calibrated parameters of the wage function with the empirical distribution of inventors. The coefficient estimate in column (1) of Table 7 confirms a strong positive relationship between the return on R&D and the estimated wage elasticity, explaining about 8% of the variation with a coefficient estimate around 0.4.[32] Furthermore, column (3) confirms that this link is not driven a general correlation between inventor employment and R&D returns. This exercise, thus, suggests that the calibrated wage formulation indeed captures the relationship between inventor employment and R&D returns well, and that the associated labor market imperfections are indeed a potential driving forces behind R&D return dispersion.

[32]Note that the coefficient estimate is about one third the model implied elasticity. The difference could be driven by other factors influencing R&D returns or measurement error in inventor employment.

Table 7: Return on R&D and Implied Wage Elasticity

	(1)	(2)	(3)
		ln **Return on R&D**	
$\ln(1 + \hat{\varepsilon}_W)$	0.383***		0.304***
	(0.038)		(0.081)
ln Inventors		0.234***	0.056
		(0.032)	(0.065)
R2	0.08	0.07	0.08
Observations	11,812	11,812	11,812

Note: This table reports OLS regression coefficients. The implied inverse supply elasticity is estimated using inventor employment and calibrated parameters. Standard errors are clustered at the NAICS6 level.

Standard errors in parentheses. Significance levels: * 10% , ** 5%, *** 1%.

5.5 Results

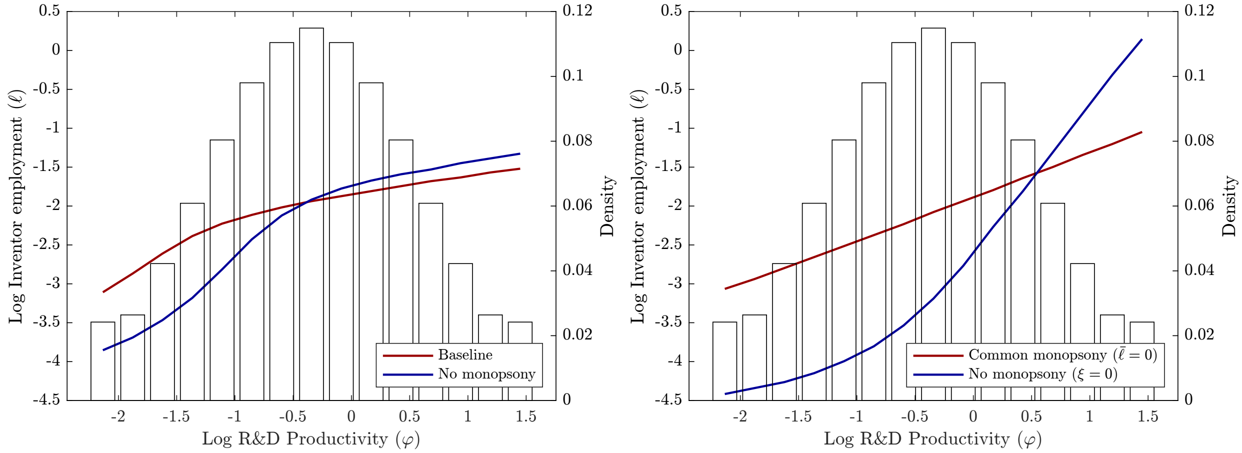
The calibrated model suggests that monopsony power is an important driver of R&D return dispersion. As reported in the first row of Table 8, log R&D returns have a standard deviation around 0.35 in the baseline calibration, which is around 1/3 of its value in the data.[33] In absence of monopsony, i.e. if firms act as price takers, R&D return dispersion is close to 0 as reported in the second row. The calibrated model, thus, suggests that heterogeneous monopsony power is a meaningful contributor to the measured dispersion.

Inventor monopsony has a significant impact on economic growth in the model. As reported in the second row of Table 8, annual growth is 4% (0.06 p.p.) faster in the model if firms took wages as given. For comparison, Lucas (2003) estimates that the cost of business cycles are around 1%, while Arkolakis et al. (2012) argue that US welfare would decrease by 1% under trade autarky. More closely connected, Berger et al. (2022) estimate welfare cost of monopsony power in production at 7.6%, while Terry (2022) reports a similar growth impact of manager short-termism. Importantly, since L is fixed, accelerating growth is entirely due to a reallocation of inventors across firms. As highlighted in Panel (a) of Figure 3, inventor employment is more sensitive to R&D productivity without monopsony power. Turning

[33] I only report values for dispersion in expected returns. Realized returns have a small measurement error component in the model, which is unrelated to the frictions driving dispersion in expected returns.

off monopsony power redistributes workers from low to high R&D productivity firms and, therefore, improves aggregate R&D productivity.

Figure 3: Policy Functions in the Calibrated Model



(a) The Power of Monopsony

(b) Common vs No Monopsony

Notes: Panel (a) plots policy functions in the baseline calibration comparing the baseline case with a world in which firms take wages as given. Panel (b) considers alternative specifications with either common monopsony power ($\bar{\ell} = 0$) at the average level of the baseline specification or no worker preferences over firms ($\xi = 0$).

I further explore the importance of worker preferences over firms, i.e. a finite firm-level labor supply elasticity, further in Panel (b), where I consider two cases. First, I consider the case of common monopsony by imposing $\bar{\ell} = 0$ and recalibrating ξ to match the average inverse labor supply elasticity in the baseline model. The new policy function is approximately log-linear and, thus, redistributes workers towards high productivity firms. As reported in row 3 of Table 8, this change accelerates growth significantly by improving aggregate R&D productivity. Importantly, monopsony power does not impact growth in this case, but instead leads to a change in the inventor wage as its effect on firm labor demand is proportional and the aggregate mass of inventors is fixed. Finally, in absence of worker preferences over firms, the allocation of researchers is much more responsive to R&D productivity as shown in Panel (b) of Figure 3. Again, this reallocation improves aggregate R&D productivity and, thus, economic growth significantly. Note, however, that the welfare implications of these alternative allocations are ambiguous if baseline labor supply elasticity reflect preferences rather than market structure or firms' attempts to differentiate jobs via amenities. On the one hand, they improve economic growth and, thus, welfare for all with the usual intertemporal externalities of knowledge creation. On the other hand, inventors are worse off due to larger abor disutility, offsetting the welfare gains from faster growth.

Table 8: Return Dispersion, Growth, and Monopsony

Model	SD	Growth-rate	Welfare
Baseline	0.35	1.50%	—
No monopsony	0.03	1.56%	2.1%
Common monopsony ($\bar{\ell} = 0$)	0.01	1.58%	2.7%
No preferences ($\xi = 0$)	0.07	1.70%	6.7%

Note: Table reports model results for main calibration and counterfactual where firms take wages as given. SD refers to the standard deviation of log R&D returns based on simulation with 100,000 periods. Welfare column quantifies growth-rate change in terms of consumption equivalent change.

Discussion - Alternative calibrations. I consider two alternative sets of target moments for calibration in Appendix C.4. First, I target the size-based estimates in column (3) of Table 4 instead of the return-based ones in column (2). Second, I replace my estimates of the inverse labor supply elasticity with Seegmiller (2021)'s estimates for high-skilled workers. Both alternative specification suggests that monopsony leads leads to significant R&D return dispersion at large growth cost. For the size-based calibration I find a standard deviation of R&D returns of 0.43 and growth acceleration in absence of monopsony of 5% (0.07 p.p.). The respective estimates for the second alternative calibration are 0.17 and 2% (0.03 p.p.), respectively. Thus, across calibrations inventor monopsony has a significant growth impact.

Discussion - Perfect price discrimination. Monopsony power arises when the firm's marginal hiring decision has an impact on its inframarginal wage. In contrast, under perfect price discrimination, firms' marginal hiring decision do not affect the wages of other workers and, thus, firms have no incentive to artificially keep their labor demand low. I show in Appendix C.5 that R&D return dispersion can still arise under price discrimination, but its source is different. Price discrimination breaks the proportionality between the average and the marginal wage leading to dispersion in the average R&D return, but not the marginal one. Thus, R&D return dispersion itself might not be a sign of misallocation if we have strong reason to believe that marginal price and benefits faced by the firms are not proportional to their averages, however, the evidence in Seegmiller (2021) suggests that marginal hiring decision for high-skilled workers do affect the wage of the existing workforce.

6 Conclusion

Workhorse endogenous growth models predict that R&D returns should be equalized in equilibrium in absence of frictions. Contrary to this prediction, I show that they are widely dispersed empirically, and persistently so. A firm at the 75th percentile of the empirical distribution earns twice the median return. Furthermore, such a firm on average still earns a return 65% larger than the median return after 5 years.

This paper argues that R&D return differences are partly due to monopsony in the inventor market. I show that R&D returns can reflect monopsony power via differences in the firm-specific inverse labor elasticity, and provide evidence in favor of this hypothesis. My estimates suggests that firms with larger R&D returns have more pricing power in the market for inventors, i.e. face less elastic inventor supply, as do firms with large inventor workforce. I find that differences in monopsony power can explain around 30% of the average return difference between below and above median R&D return firms, and the entire average return difference across below and above median inventor employment firms.

I estimate the impact of inventor monopsony on economic growth in a calibrated Schumpeterian growth model. The model accounts for 1/3 of the documented R&D return dispersion and predicts a 4% (0.06 p.p.) faster growth rate in absence of monopsony, equivalent to a 2.1% welfare improvement. Importantly, growth accelerates due to an improvement in the allocation of inventors and, thus, aggregate R&D productivity as I keep the supply of inventors fixed. The model thus suggests that R&D return dispersion is intimately linked to the allocation of inventors, aggregate R&D productivity, and economic growth.

Jointly, my findings suggest at least two avenues for future research. First, a large share of the R&D return dispersion remains unaccounted for. In companion paper Lehr (2022) I estimate their impact on economic growth in a structural growth model that admits a closed form solution under the assumption that R&D returns reflect frictions only. My estimates suggests that the documented R&D return dispersion is associated with significant cost, raising the question as to which additional drivers can account for the remaining, so far unexplained share of the overall variation. Second, inventor misallocation due to monopsony further raises the question as to its consequences for human capital accumulation. Inventors' work does not only create inventions, but also develops their human capital. If firms suppress their demand for inventors due to monopsony power, this might have important consequences for the aggregate human capital stock in the innovation sector.

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Appendix

A Data Appendix

A.1 Data Construction

Mapping patents to firms. I assign patents to firms based on the crosswalk between patents and `PERMNO`s in Kogan et al. (2017), which I extend to `GVKEY`s using the mapping provided by WRDS.

Measuring inventor employment. Let $\mathcal{P}_{it\to t+4}$ be the set of successful patent applications for firm i between t and $t+4$ and $\mathcal{I}_{it\to t+4}$ be the set of associated inventors. I will denote the number of patents assigned to firm i and listing j as inventor at time t as P_{ijt} and the total number of patents listing j as inventor as P_{jt}

$$\texttt{Inventors}_{it\to t+4} = \sum_{j\in\mathcal{I}_{it\to t+4}} \frac{\sum_{s=0}^{4} P_{ijt+s}}{\sum_{s=0}^{4} P_{jt+s}}. \tag{A.1}$$

I use two additional measure in robustness checks. Firstly, I use the raw size of $|\mathcal{I}_{it\to t+4}|$, which forgoes the full-time equivalent adjustment, and, secondly, I construct the measure first at the 1-year horizon and then aggregate over the 5-year window. Note that the former is identical to the main measure when all inventors are only listed on patents that are also assigned to the firm.

Inventor wages. I construct inventor wages as the ratio of R&D expenditure and my inventor employment measure.

$$\texttt{Inventor Wage}_{it} \equiv \frac{\sum_{s=0}^{4} \texttt{R\&D Expenditure}_{it+s}}{\texttt{Inventors}_{it\to t+4}}$$

Inventor productivity. I construct annual inventor productivity by assigning each inventor an equal share of the value created by their patents and aggregating to the inventor-year level. I then regress this measure on year and inventor fixed effects and use the latter as my long-run measure of inventor productivity. Alternatively, I add firm fixed effects to the regression based on the primary employer of the inventor and, again, use the inventor fixed effect as my measure of adjusted inventor productivity. When constructing these measures at an annual level, I exclude the years in consideration from the sample to safeguard against spurious correlation with other outcomes. I aggregate these measures to the firm-level using the full-time equivalent employment shares constructed above.

Dominance. I construct the dominance measure used in Appendix B.3 in two steps. Firstly, for each of the firm's new patent within a 5-year window, I calculate the share of inventors working for the firm among those that worked on patents of the exactly same technology class classification. For the latter, I use the complete CPC classification of the patent, which has more than 600 technology classes, which are non-exclusive at the patent level. Patents of the same technology class are thus those that have exactly the same classifications as the patent in consideration. As before, I distinguish between inventors using the USPTO disambiguation and link inventors to a firm if they are listed on a firm's new patent for the 5-year window in consideration.

Secondly, I aggregate the patent-based measure to the firm-level by taking a simple average over the firm's new patents. Note that the resulting measure is between 0 and 1 by construction with 1 implying maximal dominance and vice versa.

Specialization. I construct the specialization measure used in Appendix B.3 in two steps. Firstly, I calculate inventor specialization for a given 5-year window as the average cosine similarity between patent classifications in an inventors portfolio of new patents. I rely on CPC classifications of patents, which has more than 600 non-exclusive patent categories. For each patent I then create an indicator vector over the set of available patent classification, where I weight individual categories by their inverse frequency. I then calculate the average cosine similarity across all patents in the portfolio and take the simple average across all patents. This measure is between 0 and 1 by construction with 0 implying completely different patents and 1 implying that all patents have the same technology classification.

I aggregate this measure up to the firm-level by taking a patent-weighted average across inventor associated with a firm, where the weight reflect the number of new patents shared by the inventor and firm. I interpret a larger value in this measure as more specialized inventors and vice verse following the logic that specialized inventors work on similar patents.

B Empirical Appendix

B.1 Robustness for Return on R&D Dispersion

Return on R&D Specification. I have three main choices in the construction of the return on R&D: the time-window in consideration, the lag between R&D expenditure and patent valuations, and the minimum number of patents required. For my baseline definition in equation (1), I chose a window of 5 years, a lag of 1 year, and a minimum of 50 patents. Appendix Table B.1 confirms that neither choice is driving my results. Extending the time-window increases measured dispersion for the return on R&D, but not for alternative return measures, such that the difference is even more pronounced at longer time-windows. Similarly, extending the lag between patent valuations and R&D expenditure increases the dispersion in the measured Return on R&D. Finally, requiring at least 200 patents reduces the dispersion in the return on R&D by about 8%, however, the sample selection reduces the dispersion in the return on capital even faster such that the relative gap increases.[34]

Stochastic realizations. The realization of R&D expenditure might have a stochastic component, which could yield dispersion in measured R&D returns. I investigate this concern by assuming that a share $P_h(p)$ of R&D expenditure is realized at horizon h, where P_h is the geometric distribution:

$$P_h(p) = \frac{(1-p)^{h-1} \cdot p}{1-(1-p)^{\bar{\Delta}}} \quad \text{for} \quad h = 1, ..., \bar{\Delta} \quad \text{with} \quad \bar{\Delta} = 10.$$

The relevant R&D expenditure for innovation at time t is then given by

$$\text{R\&D}^p_{it-1} = \sum_{h=1}^{\bar{\Delta}} \text{R\&D}_{t-s} \cdot P_h(p),$$

and the value associated with R&D investment at time $t-1$ is given by

$$\text{Valuation}^p_{it} = \sum_{h=1}^{\bar{\Delta}} \frac{\text{R\&D}_{it-1} \cdot P_h}{\text{R\&D}^p_{it-1+h}} \cdot \text{Valuation}_{it+h-1}.$$

[34] In Appendix B.1 I allow the benefits of R&D to be distributed across time to account for the probabilistic nature of innovation. The measured dispersion is at best marginally lower under this alternative assumption.

I then construct alternative measures of R&D return at the 5-year window as

$$\text{Expected Return on R\&D}_{it}^{p} \equiv \frac{\sum_{s=0}^{4} \text{Valuation}_{it+s}^{p}}{\sum_{s=0}^{4} \text{R\&D Expenditure}_{it-h+s}}. \tag{B.1}$$

Note that $p = 100\%$ recovers the baseline case.

Table B.2 confirms that the large dispersion of R&D returns and its gap with respect to other measures of return dispersion is highly robust to this alternative specification. For example, a steep, but not instantaneous decay of $p = 95\%$ reduces the dispersion in the Return on R&D marginally, while leaving it more than 40% larger than the Return on Capital. Particularly slow decays increase the dispersion in measured R&D returns.

Table B.1: Return Dispersion Across Specifications

Specificaton	Return on R&D	Return on Capital	
	SD	SD	Δ%
A. Time-window			
5-year	1.11	0.77	43.4%
10-year	1.14	0.75	51.6%
20-year	1.16	0.72	61.6%
B. Minimum patents			
50 patents	1.11	0.77	43.4%
100 patents	1.04	0.71	45.3%
200 patents	1.02	0.68	50.6%
C. Realization lag			
1-year	1.11	0.77	43.4%
3-year	1.20	0.79	51.6%
5-year	1.28	0.79	62.3%

Note: Baseline specification is a horizon of 5 years with at least 50 patents and a 1-year realization lag. Dispersion calculated for sample without missing observations across return measures. Column headers SD report standard deviations of return measure. Column (3) reports the difference of Return on R&D and Capital dispersion relative to Return on Capital dispersion. Returns are measured in logs.

Table B.2: Return Dispersion with Realization Distribution Function

Decay	Return on R&D	Return on Capital		Return on Labor	
Factor p	SD	SD	$\Delta\%$	SD	$\Delta\%$
100%	1.11	0.77	43.4%	0.79	39.6%
90%	1.09	0.76	43.3%	0.79	38.2%
75%	1.10	0.76	44.2%	0.79	39.7%
50%	1.14	0.77	48.0%	0.79	43.8%
25%	1.20	0.78	53.7%	0.79	51.1%

Note: Return on R&D assumes decay factor indicated in first column. Alternative return measures are constructed using their original definition, but only taken into account returns when the Return on R&D is non-missing. Column headers SD report standard deviations of return measure. Columns headers $\Delta\%$ indicate percent difference of Return on R&D dispersion with respect to return in consideration. Returns are measured in logs.

Output and input definition. One potential concern with the measured R&D return is that output or input measures might not be comprehensive. On the output side, one might be concerned that patent valuations do not capture all the reward of conducting R&D (Cohen and Klepper, 1996). To address this concern, I follow Bloom et al. (2020) and construct alternative measure of R&D output based on positive changes in revenue, employment, or labor productivity defined as revenue per employee. The alternative measures of the Return on R&D are thus defined as

$$\text{R\&D Return}_{it}^{X} \equiv \frac{\sum_{s=0}^{4} \max\{\text{X}_{it+s} - X_{it-1+s}, 0\}}{\sum_{s=0}^{4} \text{R\&D Expenditure}_{it-1+s}} \qquad \text{with} \quad \text{X} \in \{\text{Revenue, Employment, Labor Productivity}\}. \tag{B.2}$$

As reported in Panel A of Table B.3, the dispersion using these alternative measures of R&D output turns out to be larger compared to the dispersion in the baseline measure. Thus, Return on R&D dispersion measured using patent valuation is a conservative estimate.

Table B.3: Return Dispersion with Alternative Meausures of R&D Output and Input

	R&D Return	Return on Capital	
	SD	SD	Δ%
A. Alternative Output			
Patent valuations	1.11	0.77	43.4%
Revenue changes	1.41	0.77	83.7%
Employment changes	1.71	0.77	122.8%
Labor productivity changes	1.73	0.76	126.6%
B. Alternative Input			
R&D Expenditure	1.11	0.77	43.4%
Knowledge capital	1.14	0.77	48.0%

Note: Return on R&D calculated using output definition indicated in first column. Alternative return measures are constructed using their original definition, but only taken into account returns when the Return on R&D is non-missing. Column headers SD report standard deviations of return measure. Columns headers Δ% indicate percent difference of Return on R&D dispersion with respect to return in consideration. Returns are measured in logs.

On the input side, we might be concerned that R&D expenditure does not capture all the inputs associated with the firm's innovation activity. For example, the literature on intangible capital has argued that overhead expenses also serve to enhance a firm's productive capacity, which might be partly reflected in its patent valuation. Building on this insight, I use the knowledge capital series from Ewens et al. (2020), which reflects discounted R&D and overhead expenses, to construct an alternative measure of the Return on R&D as

$$\text{R\&D Return}_{it}^{K} \equiv \frac{\sum_{s=0}^{4} \text{Patent valuations}_{it+s}}{\sum_{s=0}^{4} \text{Knowledge capital}_{it-1+s}}. \tag{B.3}$$

Panel B in Table B.3 confirms that the Return on R&D remains highly dispersed using the alternative input measure. In fact, the dispersion increases slightly from 1.11 to 1.14.

B.2 Measurement Error

Dispersion in R&D returns could be due to measurement error arising, e.g., from the expectation-realization gap, patent valuation estimation, or misreporting of R&D expenditure.[35] In this section I propose two complementary approaches to estimating the contribution of measurement error to measured Expected Return on R&D dispersion. I begin by taking a structural approach using a GMM estimator to investigate the importance of classical measurement error. In addition, I use bootstrapping to estimating the potential measurement error due the uncertainty around patent valuations.

GMM Estimation of Measurement Error. Consider a stationary, AR(1) process $\{y_{it}\}$:

$$y_{it} = (1-\rho)\mu_i + \rho y_{it-1} + \varepsilon_{it} \quad \text{with} \quad \varepsilon_{it} \overset{iid}{\sim} N(0, \sigma_\varepsilon^2) \quad \text{and} \quad \mu_i \sim N(0, \sigma_\mu^2). \tag{B.4}$$

The econometrician observes the process with i.i.d. normal measurement error:

$$\tilde{y}_{it} \equiv y_{it} + \nu_{it} \quad \nu_{it} \overset{iid}{\sim} N(0, \sigma_\nu^2). \tag{B.5}$$

Lemma B.1. *Define $\Delta\tilde{y}_{it} \equiv \tilde{y}_{it} - \tilde{y}_{it-1}$, then under $\rho \in (0,1)$, we have*

$$\begin{aligned}
m_1 &\equiv Cov(\tilde{y}_{i,t}, \Delta\tilde{y}_{it}) = \frac{1}{1+\rho}\sigma_\varepsilon^2 + \sigma_\nu^2 \\
m_2 &\equiv Cov(\tilde{y}_{i,t}, \Delta\tilde{y}_{it-1}) = \frac{\rho}{1+\rho}\sigma_\varepsilon^2 \\
m_3 &\equiv Cov(\tilde{y}_{i,t}, \Delta\tilde{y}_{it-2}) = \frac{\rho^2}{1+\rho}\sigma_\varepsilon^2 \\
m_4 &\equiv Cov(\tilde{y}_{i,t}, \tilde{y}_{it-1}) = \sigma_\mu^2 + \frac{\rho}{1-\rho^2}\sigma_\varepsilon^2.
\end{aligned}$$

Proposition B.1. *If $\rho \in (0,1)$, we can solve for $\{\rho, \sigma_\mu, \sigma_\varepsilon, \sigma_\nu\}$ using the population auto-*

[35] Note that R&D expenditure is expensed in US GAAP accounting, giving firms an incentive to fully report R&D expenditure to reduce their tax liability. Terry et al. (2022) argue that managers still might misreport when attempting to hit short-run earnings targets or smooth earnings. See also Dukes et al. (1980); Baber et al. (1991); Lev et al. (2005); Chen et al. (2021); Terry (2022).

covariance structure of $\tilde{y}_{it}$ and $\Delta\tilde{y}_{it} \equiv y_{it} - y_{it-1}$:

$$\beta \equiv \begin{bmatrix} \rho \\ \sigma_\varepsilon^2 \\ \sigma_\mu^2 \\ \sigma_\nu^2 \end{bmatrix} = \begin{bmatrix} \frac{m_3}{m_2} \\ \frac{(m_2)^2}{m_3} + m_2 \\ m_4 - \frac{(m_2)^2}{m_2 - m_3} \\ m_1 - \frac{(m_2)^2}{m_3} \end{bmatrix}$$

Let Ω be the covariance matrix of m and denote the sample moments by $\hat{m}$, then

$$\hat{\beta} \sim N(\beta, \Sigma) \quad \textit{and a feasible estimator is} \quad \hat{\Sigma} = \left(\frac{\partial\hat{\beta}}{\partial m}\right)' \hat{\Omega} \left(\frac{\partial\hat{\beta}}{\partial m}\right),$$

where $\partial\beta/\partial m$ is evaluated at $\hat{m}$ and given by

$$\frac{\partial\beta}{\partial m} = \begin{bmatrix} 0 & 0 & 0 & 1 \\ -\frac{m_3}{(m_2)^2} & 2\frac{m_2}{m_3} + 1 & m_2\left(\frac{m_2 - 2m_3}{(m_2 - m_3)^2}\right) & -2\frac{m_2}{m_3} \\ \frac{1}{m_2} & -\left(\frac{m_2}{m_3}\right)^2 & -\left(\frac{m_2}{m_2 - m_3}\right)^2 & -\left(\frac{m_2}{m_3}\right)^2 \\ 0 & 0 & 1 & 0 \end{bmatrix}.$$

Proof. The first part follows by rearranging the moments expressions. The second part follows from the Law of Large Numbers for the moment vector and the Delta method. □

Note that this methodology does not aggregate. In particular, if we assume that expected R&D return follows an AR(1) in logs at the annual level, we cannot implement the above methodology at the 5-year horizon directly as the 5-year expected R&D return is a weighted-average of the annual return in levels, which does not translate into logs:

$$\frac{\sum_{s=0}^4 \text{Pat. Val.}_{it+s}}{\sum_{s=0} \text{R\&D Exp.}_{it-1+s}} = \sum_{s=0}^{4} \frac{\text{R\&D Exp.}_{it-1+s}}{\sum_{w=0} \text{R\&D Exp.}_{it-1+w}} \times \frac{\text{Pat. Val.}_{it+s}}{\text{R\&D Exp.}_{it-1+s}}.$$

To address this concern, I will estimate the system at the 1-year level and propose a methodology to estimate the importance of measurement error at the 5-year level. I restrict my sample to 1-year returns with at least 10 patents in line with the requirement that R&D returns should have at least 50 patents over a 5-year period..

The GMM estimates presented in Table B.4 suggest that measurement error constitutes little of the overall variation in the 1-year R&D return. The estimated measurement error variation is around 0.04 and significant at the 5% level. In addition, I find that the Return on R&D is highly auto-correlated with significant variation due to idiosyncratic shocks. The estimates suggests that permanent difference constitute little of the overall variation,however, the standard errors around the estimate for σ^2_μ are very large.

Table B.4: GMM Estimates

Parameter	Estimate
ρ	0.892***
	(0.062)
σ^2_ε	0.170***
	(0.020)
σ^2_μ	-0.046
	(0.861)
σ^2_ν	0.044**
	(0.017)
Observations	7,553

Note: Standard errors clustered at the NAICS6 level and reported in brackets.

As discussed before, we cannot immediately translate these estimates into measurement error contributions at the 5-year level due to aggregation. I address this challenge by adding some structure on the firm R&D process. In particular, I will assume that each firm in my data solves the simple maximization problem

$$\max_{\ell_{it}} \left\{ \varphi \ell_{it}^{\gamma} - \Delta_{it} \times W \ell_{it} \right\}. \tag{B.6}$$

The source of R&D returns in this framework is Δ_{it} and I consequently assume that it follows an AR(1) process, which the researcher observed with i.i.d. measurement error.

Lemma B.2. *Under above assumptions, the 5-year Return on R&D is given by*

$$\textit{Expected Return on R\&D}_{it} = \frac{1}{\gamma} \times \frac{\sum_{s=0}^{4} \Delta_{it}^{-\frac{1+\phi}{\phi}} \times \tilde{\Delta}_{it}}{\sum_{s=0}^{4} \Delta_{it}^{-\frac{1+\phi}{\phi}}}.$$

Proof. The solution to the firm optimization problem is given by

$$\ell_{it} = (\Delta_{it} W)^{\frac{1}{\gamma-1}} \times (\varphi\gamma)^{\frac{1}{1-\gamma}}$$

The annual return on R&D is proportional to Δ_{it}:

$$\frac{\varphi \ell_{it}^{\gamma}}{W\ell_{it}} = \frac{1}{\gamma} \times \Delta_{it}.$$

By definition, we can then express the overall return as measured in the data as

$$\frac{\sum_{s=0}^{4} W\ell_{it+s} \times \tilde{\Delta}_{it+s}}{\sum_{s=0}^{4} W\ell_{it+s}} = \frac{1}{\gamma} \times \frac{\sum_{s=0}^{4} \Delta_{it}^{-\frac{1}{1-\gamma}} \times \tilde{\Delta}_{it}}{\sum_{s=0}^{4} \Delta_{it}^{-\frac{1}{1-\gamma}}}.$$

□

Using this framework, we can simulate data based on the estimates in B.4 and aggregate to the 5-year level as suggested above. To estimate the importance of measurement error, we can then compare baseline estimates against a counterfactual with $\sigma_{\nu}^2 = 0$. I follow the literature and set $\gamma = 0.5$ for the purpose of this exercise Acemoglu et al. (2018).

Table B.5 reports the results, which suggest that measurement error makes a minor contribution to the dispersion in the Expected Return on R&D. I find that measurement error contributes less than 1% to the overall dispersion in the 5-year expected R&D return. The importance of measurement error is decreasing in the time-horizon considered as the individual shocks average out.

Table B.5: Disperion in Simulated Expected Return on R&D

Measure	1-year	5-year
SD	0.937	0.854
SD with $\sigma_{\nu}^2 = 0$	0.913	0.848
Δ%	2.5%	0.7%

Note: The first data row reports the standard deviation of the simulated Expected Return on R&D using the associated GMM parameter estimates. The second row recalculates this dispersion imposing no measurement error or $\sigma_{\nu}^2 = 0$. The final row reports the reduction in the dispersion of the Expected Return on R&D due to the reduction in measurement error.

Bootstrap Estimation for Valuation Uncertainty. In addition to the investigation of classical measurement error, I consider the role of patent valuation uncertainty explicitly. In a bootstrap procedure I redraw patent valuations from the realized patent portfolio and construct Returns on R&D assuming that the first targets a return proportional the expected value of patent valuations ex-ante. Repeating this exercise for 1000 iteration I then calculate an estimated dispersion in the measured Expected Return on R&D based on uncertain valuation outcomes only.

Each iteration in my procedure proceeds as follows:

1. For each firm and 5-year window in which the firm has at least 50 patents:
   (a) From the portfolio of patent valuations for the firm-period, draw with replacement an alternative portfolio with as many valuations as the firm had patents in the period.
   (b) Calculate the return as the ratio the valuations in the alternative portfolio divided by the valuation of the true portfolio.
2. Calculate the standard deviation of Return on R&D for the simulated data.

I repeat this procedure until I have 1000 bootstrap estimates of the standard deviation of Returns on R&D. Note that the resulting dispersion in the Return on R&D is driven exclusively by the variability of patent valuations and would yield 0 variation if all patents had the same value.

One way to interpret this approach is that the realized patent portfolio is a good approximation for the true uncertainty faced by the firm around its innovation outcomes. The procedure ignores all variation coming from shifts in the level of expected patent valuation and instead considers the dispersion conditional on the average value only. As a result, the procedure will overstate the associated measurement error if firms are aware that certain project are low or high expected value within their research portfolio.

Table B.6 reports estimates suggesting that the measurement error due to patent valuation uncertainty could account for up to $0.067/1.1 = 6\%$ of the standard deviation of the measured Expected Return on R&D. Unsurprisingly, the estimated measurement error declines with the size of the minimum patent portfolio and is precisely estimated with tight confidence intervals.

Table B.6: Measurement Error Estimates using Bootstrap Procedure

Minimum patents	Estimate	Standard error	95% Confidence Interval
30	0.08	(0.002)	[0.077,0.084]
50	0.067	(0.002)	[0.064,0.071]
100	0.051	(0.001)	[0.049,0.053]
200	0.042	(0.001)	[0.04,0.045]

Note: Measurement error estimates based on distribution of patent valuations for different cut-offs levels of minimum patent counts.

B.3 Additional Evidence on Systematic Drivers

Investment and Financial Frictions. A large and growing literature documents dispersion in the return on capital and links it to investment and financial frictions.[36] If firms have limited ability to borrow or face very high cost of external finance, they will forgo marginal investment opportunities and earn high returns as a result. As long as firms differ in their investment opportunities and/or access to external finance, this mechanism gives rise to dispersion in the return on capital.

The same rationale may apply to R&D investment, making financial frictions an intriguing candidate mechanism to explaining R&D return dispersion. According to this theory, financially constrained firms limit their R&D expenditure leading to high returns they forgo funding mediocre projects at the margin.[37] I investigate this link in an OLS framework:

$$\text{Expected Return on R\&D}_{it} = \alpha_{j(i)\times t} + \beta \text{Friction Measure}_{it} + \varepsilon_{it}. \tag{B.7}$$

If financial frictions are quantitatively important, we would expect $\beta > 0$, i.e. constrained firms have high returns, together with a large R^2. I will use the return on capital as my primary measure for financial frictions together with alternative proxies inspired by the literature including (1) a dummy for whether the firm is listed for less than 20 year, since

[36] Restuccia and Rogerson (2008) and Hsieh and Klenow (2009) first documented that there appears to be large dispersion in the return on capital across firms, especially so in developing countries. Asker et al. (2014); Midrigan and Xu (2014); David et al. (2016); David and Venkateswaran (2019); David et al. (2021) link this dispersion to investment and financial frictions.

[37] I formalize the link between R&D returns and financial frictions in Appendix ??.

young firms are considered to be more constrained, (2) a dummy for whether the firm is not paying dividends, since foregoing dividend payments is considered to be a sign of financial hardship, and (3) the ratio of cash holdings to assets, since more liquid firms are considered to be less financially constrained (Whited and Wu, 2006; Midrigan and Xu, 2014).

Table B.7: Return on R&D and Measures of Investment Frictions

	(1)	(2)	(3)	(4)
	Expected R&D Return			
Return on Capital	0.047			
	(0.067)			
Young Firm		-0.246**		
		(0.098)		
No Dividend Payout			-0.187***	
			(0.047)	
Liquidity				-0.047**
				(0.022)
R2	0.001	0.006	0.006	0.002
Observations	11,844	11,845	11,845	10,635

Note: This table reports OLS coefficient estimates. "Mature Firm" and "Dividend Payout" are indicators variable for firm age in Compustat of 20 years or more and positive dividend payments respectively. Liquidity measures the firms cash holdings relative to its book assets. Return and liquity are measured in logs. All regressions control for NAICS3$\times$ Year effects and standard errors are clustered at the NAICS6 level.

Standard errors in parentheses. Significance levels: * 10% , ** 5%, *** 1%.

The estimates in Table B.7 suggest that financial frictions do not drive dispersion in R&D returns. Firstly, I find a small and insignificant correlation with the return on capital. Firms that appear to be constrained in their capital investment do not systematically also appear to be constrained in their R&D investment. Secondly, firms that are young or forego paying dividends have lower returns, which is the opposite of what we would expect if returns on R&D were driven by financial constraints. Finally, liquidity has the expected sign, however, the its explanatory power is low. Financial frictions are thus not quantitatively important for R&D returns, which may be surprising in light of a growing literature arguing that R&D investments are especially vulnerable to them (Brown et al., 2009; Peters and Taylor, 2017; Ewens et al., 2020). My evidence thus adds context to the research on the interaction of financial frictions and intangible capital investments.

Risk. Inspired by David et al. (2021), I investigate the importance of risk for R&D returns using four risk proxies. Firstly, I use the CAPM β from WRDS. Secondly, I estimate the long-run firm β directly. Finally, I calculate innovation specific βs capturing the covariance of R&D returns with the stock market.

To estimate the long-run firm β, I first calculate the annual stock market return for the firm and the S&P500 index. I subtract the risk free rate from both to construct excess returns and regress the firm-specific excess return on the market excess return firm-by-firm to construct firm-level stock market βs. For the innovation-based measures I follow a similar approach, but replace firms' stock market return with the Return on R&D. I calculate this measure for both the 1-year and 5-year Return on R&D, where I restrict both to observations with at least 5 patents. I then regress the innovation-based excess returns on the market return firm-by-firm to construct firm-specific, innovation-based risk factors $\beta_{R\&D}$.

Table B.8 reports the OLS regression results relating the risk measures to the Expected Return on R&D. I find no correlation with the general, stock return-based risk measures, but significant correlations with the innovation specific risk factors.

Table B.8: Return on R&D and Firm-level Risk

	(1)	(2)	(3)	(4)
		Return on R&D		
Compustat β_{CAPM}	0.005			
	(0.060)			
$\hat{\beta}_{CAPM}$		-0.041		
		(0.078)		
1-year $\hat{\beta}_{R\&D}$			0.021***	
			(0.003)	
5-year $\hat{\beta}_{R\&D}$				0.015***
				(0.005)
R2	0.40	0.30	0.35	0.32
Within R2	0.00	0.00	0.08	0.02
Observations	6,797	10,164	9,587	9,858

Note: All regressions control for NAICS3 $\times$ year fixed effects. All returns are in logs. Standard errors clustered at the NAICS6 level.

Standard errors in parentheses. Significance levels: * 10% , ** 5%, *** 1%.

State and university partnerships. State involvement and university partnerships can create measured R&D return dispersion unconnected to economic fundamentals if they lead to inaccurate measurement of R&D inputs and outputs. For example, R&D subsidies reduce the effective cost of R&D to the firm, which is not reflected in gross R&D expenditure as reported in the firms accounting statements. Similarly, suppose the firm engage in a research partnership with a university with the agreement that all patents are assigned to the firm. Again, this scenario could lead us to under-count the true cost of R&D associated with inventions or alternatively overstate the value created by the firm's own R&D expenditure.

I explore the empirical relevance of these concerns in a simple regression framework, where I, as in the case of financial frictions, estimate how important proxies for these collaboration are for explaining R&D returns. I construct two complementary set of proxies. First, I directly identify inventions created with state support or university partnerships using patent records. I classify assignees into governmental institutions, universities, or neither based on the listed name using key words such as "university" or "federal agency". Furthermore, I classify patents as government related if they have a public interest statement, which indicates that a federal agency has supported the invention and/or has remaining rights over the patent. Following this procedure, I can then classify whether a patent is related to a government agency, university, or neither, and calculate their share of total new patent valuations. Second, I construct direct proxies of R&D subsidies using the data on state-level R&D subsidies in Lucking (2019), where I map firms to states either via their headquarter location or the distribution of inventors associated with the firms' patents as recorded in Berkes (2016).

Table B.9 confirms that neither proxy explains a significant share of the variation in R&D returns. For the first set of proxies, columns (1) and (2) suggests that firms with more state-involvement indeed have larger R&D returns, however, the coefficient is imprecisely estimated and the R^2 less than 1%. For the direct proxies of state-level R&D subsidies, I find that the coefficient does not have the predicted sign as shown in columns (3) and (4). Firms receiving less subsidies actually have higher returns and vice versa. Again, the coefficients are highly imprecise and the R^2 well below 1%. Thus, my proxies of state involvement do not account for a significant share of the variation in R&D returns. Note that this does not necessary imply that subsidies are not important. For example, we might expect such an empirical finding if state subsidies offset other friction in the innovation sector.

Table B.9: R&D Returns and Subsidies

	(1)	(2)	(3)	(4)
	R&D Return			
Public value share	0.784			
	(0.519)			
State value share		1.111		
		(0.716)		
$1-\tau$ (Headquarters)			-0.170	
			(0.574)	
$1-\tau$ (Inventors)				-0.467
				(0.617)
R2 Within	0.002	0.003	0.000	0.000
Observations	11,845	11,845	11,497	11,237

Note: All regressions control for NAICS3 × year fixed effects. R&D returns and subsidy rates are in logs. Standard errors clustered at the NAICS6 level.

Standard errors in parentheses. Significance levels: * 10% , ** 5%, *** 1%.

Labor Market Dominance. Labor market dominance has been closely connected with labor market power (Berger et al., 2022; Yeh et al., 2022). Furthermore, dominance has the added feature that it connects labor market power with firm size. I construct a measure of labor market dominance in the market for inventors to investigate the potential connection between dominance and R&D returns. For each new patent in a firm's portfolio I calculate the share of potential inventors that are working with the firm, where I classify someone as a potential inventor if they work on patents with the identical technology classification. I then average this measure out over all of the firm's patent to get a measure of overall inventor market dominance. See Appendix A for further details on the construction.

Column (1) in Table B.10 reports the OLS coefficient of a regression of the R&D return on the dominance measure. In line with a monopsony interpretation, I find that dominant firms have higher returns. A one standard deviation higher dominance measure is associated with 14% larger return.[38] A potentially confounding factor is firm size, which could be linked to returns through alternative mechanisms. Column (2) confirms that the link between

[38]The standard deviation of ln Dominance is 1.01 s.t. $1.01 \times 0.14 \approx 0.14$. In turn, $\exp(0.14) - 1 \approx 14\%$.

dominance and returns remains strong even when controlling for inventor employment.

Table B.10: Return on R&D, Labor Market Dominance, and Specialization

	(1)	(2)	(3)	(4)
	ln **Return on R&D**			
ln Dominance	0.140***	0.098**		
	(0.041)	(0.040)		
ln Specialization			0.300***	0.282***
			(0.090)	(0.087)
ln Inventors		0.222***		0.221***
		(0.035)		(0.032)
R2	0.01	0.08	0.01	0.07
Observations	10,444	10,444	11,795	11,795

Note: This table reports OLS regression coefficients. See Appendix A for variable definitions. Standard errors are clustered at the NAICS6 level.

Standard errors in parentheses. Significance levels: * 10% , ** 5%, *** 1%.

Inventor Specialization. Inventor specialization is another potential source of employer bargaining power as it reduces the set of potential employers. I investigate its relationship with R&D returns by aggregating inventor-level specialization measures to the firm-level. For an individual inventor, I construct a specialization measure based on the cosine distance between the technology classifications of patents that the inventor worked on over the period. I then average this measure to the firm-level by taking a patent-weighted average over inventors associated with the firm. See Appendix A for further details on the construction.

Column (3) in Table B.10 reports the OLS coefficient of a regression of the R&D return on the specialization measure. Indeed, I find that firms with more specialized inventors have higher returns on R&D, which supports a labor market power interpretation. A one standard deviation larger specialization measure is associated with an 8% larger return on R&D. As shown in column (4), this relationship is not driven by firm-size differences.

B.4 Labor Supply Elasticity Estimates

Table B.11 reports the first-stage results for the main specification. In addition I report results for the specification controlling for lagged wage and employment growth in Table B.14. This specification is similar to the main specification in Seegmiller (2021).

Table B.11: Inventor Inverse Labor Elasticity Estimates — First Stage

	(1)	(2)	(3)
A. Main		$\Delta \ln \texttt{Inventors}_{it}$	
Stock Return$_{it}$	0.065***	0.042***	0.065***
	(0.007)	(0.009)	(0.010)
— × {Top 50% R&D Return}		0.042***	
		(0.011)	
— × {Top 50% Inventors}			0.001
			(0.011)
B. Interaction		$\Delta \ln \texttt{Inventors}_{it} \times$ **{Top 50% R&D Return$_{it}$}**	
Stock Return$_{it}$		0.002	0.007**
		(0.002)	(0.003)
— × {Top 50% R&D Return}		0.047***	
		(0.007)	
— × {Top 50% Inventors}			0.039***
			(0.008)
First stage F stat. (Main)		39	48
First stage F stat. (Inter.)		39	48
Observations	14,834	14,834	14,834

Note: First stage regression results for main specification. All regressions control for NAICS3 × year fixed effects. Standard errors clustered at the NAICS6 level.

Standard errors in parentheses. Significance levels: * 10% , ** 5%, *** 1%.

Table B.12: Inventor Inverse Labor Elasticity Estimates

	(1)	(2)	(3)	(4)
		$\Delta \ln$ **`Inventor Wage`**$_{it}$		
$\Delta \ln$ `Inventors`	0.817**	0.814**	0.410**	0.405**
	(0.325)	(0.327)	(0.203)	(0.200)
— $\times$ {Top 50% R&D Return}	1.079**	1.093**		
	(0.512)	(0.517)		
— $\times$ {Top 50% Inventors}			1.245***	1.268***
			(0.446)	(0.447)
{Top 50% R&D Return}	-0.224***	-0.224***		
	(0.044)	(0.044)		
{Top 50% Inventors}			-0.090***	-0.088***
			(0.020)	(0.020)
Δ Inventor Productivity		0.077*		0.083**
		(0.040)		(0.038)
First stage F stat. (Main)	39	40	48	48
First stage F stat. (Inter.)	60	59	71	69
Observations	14,834	14,834	14,834	14,834

Note: This reports the second stage results for the main specification with and without inventor productivity controls. Firm-level inventor productivity is calculated as the average inventor productivity among current inventors, where individual inventor's productivity is simply their long-run average annual value created. All regressions control for NAICS3 $\times$ year fixed effects. Standard errors clustered at the NAICS6 level.

Standard errors in parentheses. Significance levels: * 10% , ** 5%, *** 1%.

Table B.13: Inventor Inverse Labor Elasticity Estimates With Firm Fixed Effects

	(1)	(2)	(3)
		$\Delta \ln$ **`Inventor Wage`**	
$\Delta \ln$ `Inventors`	1.502***	1.268***	0.819**
	(0.379)	(0.428)	(0.318)
— × {Top 50% R&D Return}		2.053**	
		(0.797)	
{Top 50% R&D Return}		-0.369***	
		(0.073)	
— × {Top 50% Inventors}			1.717***
			(0.537)
{Top 50% Inventors}			-0.191***
			(0.042)
First stage F stat. (Main)	44	31	35
First stage F stat. (Inter.)		43	64
Observations	14,816	14,816	14,816

Note: All regressions control for firm effects and NAICS3 × year fixed effects. Standard errors clustered at the NAICS6 level.

Standard errors in parentheses. Significance levels: * 10% , ** 5%, *** 1%.

Table B.14: Inventor Inverse Labor Elasticity Estimates With Controls

	(1)	(2)	(3)	(4)
A. Second stage		$\Delta \ln \texttt{Inventor Wage}_{it}$		
$\Delta \ln \texttt{Inventors}_{it}$	4.826***	3.818***	4.570***	3.620***
	(0.980)	(0.981)	(1.045)	(0.931)
— × {Top 50% R&D Return$_{it}$}		2.352***		2.950**
		(0.816)		(1.228)
{Top 50% R&D Return$_{it}$}		-0.142***		-0.201***
		(0.050)		(0.063)
B. First Stage: Main		$\Delta \ln \texttt{Inventors}_{it}$		
Stock Return$_{it}$	0.066***	0.023***	0.022***	0.025***
	(0.006)	(0.005)	(0.004)	(0.006)
— × {Top 50% R&D Return$_{it}$}		0.002		-0.006
		(0.006)		(0.007)
C. First Stage: Interaction		$\Delta \ln \texttt{Inventors}_{it}$ × **{Top 50% R&D Return$_{it}$}**		
Stock Return$_{it}$		-0.005		-0.004
		(0.003)		(0.002)
— × {Top 50% R&D Return$_{it}$}		0.034***		0.027***
		(0.007)		(0.005)
Firm Effects			✓	✓
First stage F stat. (Main)		37		32
First stage F stat. (Inter.)		37		32
Observations	14,044	14,044	14,028	14,028

Note: All regression control for lagged inventor wage and employment growth as well as current inventor productivity growth. All regressions control for NAICS3 × year fixed effects. Standard errors clustered at the NAICS6 level.

Standard errors in parentheses. Significance levels: * 10% , ** 5%, *** 1%.

C Model Appendix

C.1 Proofs and Further Results for Section 5

Definition 3. *A Balanced Growth Path equilibrium is a competitive equilibrium such that prices W_t and quantities $\{Y_t, A_t\}$ grow at a constant rate g and R_t is a constant.*

As summarized in Proposition C.1, the model formulation allows me to decompose the value function into a profit and R&D component. The former captures the expected net-present-value of the profits associated with existing leadership positions. The latter capture the value of the firm's ability to conduct R&D and create leadership positions in the future. The assumption delivering this property is the fixed R&D production function.

Proposition C.1. *Along the BGP, the normalized value function $V(\cdot) \equiv V_t(\cdot)/Y_t$ is constant and can be decomposed into a profit and R&D component:*

$$V(\cdot) = \sum_{j \in \mathcal{J}_{it}} \mathcal{V}(\lambda_{jt}) + \tilde{V}(\ell_{it-1}, \varphi_{it}) \tag{C.1}$$

The profit component is equivalent to the expected discounted sum of profits:

$$\mathcal{V}(\lambda_{jt}) = \frac{\pi(\lambda_{jt})}{1 - \beta(1-z)} \qquad \text{with} \qquad \pi(\lambda_{jt}) = 1 - 1/\lambda_{jt}. \tag{C.2}$$

The R&D component is the solution to the value function maximization problem

$$\tilde{V}(\ell_{it-1}, \varphi_{it}) = \max_{\ell_{it}} \left\{ -C(\ell_{it-1}, \ell_{it}) + \beta \left(z_{it} \mathbb{E}_\lambda[\mathcal{V}(\lambda)] + \mathbb{E}_t[\tilde{V}(\ell_{it}, \varphi_{it+1})] \right) \right\}, \tag{C.3}$$

where expectations $\mathbb{E}_t[\cdot]$ are taken with respect to the productivity process only and expectation $\mathbb{E}_\lambda[\cdot]$ capture the distribution over λ.

Proof of Proposition C.1. Firstly, we can guess and verify that the value function is proportional to Y_t, since profits are proportional to Y_t and cost are proportional to W_t with $W \equiv W_t/Y_t$ being constant along the balanced growth path by assumption. The Euler equation then implies $\frac{1+g}{R} = \beta$ and we have

$$V(\mathcal{A}_{it}, \varphi_{it}, \ell_{it-1}) = \max_{\ell_{it}} \Big\{ \sum_{j \in \mathcal{J}_{it}} \pi(\lambda_{jt}) - C(\ell_{it-1}, \ell_{it}) + \beta \mathbb{E}_t \big[V(\mathcal{A}_{it+1}, \varphi_{it+1}, \ell_{it}) \big] \Big\}, \tag{C.4}$$

where $C(\ell_{it-1}, \ell_{it}) \equiv C_t(\ell_{it-1}, \ell_{it})/Y_t$.

Secondly, we can guess and verify

$$
\begin{aligned}
& V(\mathcal{A}_{it}, \varphi_{it}, \ell_{it-1}) = \tilde{V}(\varphi_{it}, \ell_{it-1}) + \sum_{j \in \mathcal{J}_{it}} \mathcal{V}(\lambda_{jt}) \qquad \text{with} \\
& \tilde{V}(\ell_{it-1}, \varphi_{it}) = \max_{\ell_{it}} \left\{ -C(\ell_{it-1}, \ell_{it}) + \beta \left(z_{it} \mathbb{E}_{\lambda}[\mathcal{V}(\lambda)] + \mathbb{E}_t[\tilde{V}(\ell_{it}, \varphi_{it+1})] \right) \right\} \\
& \mathcal{V}(\lambda_{jt}) = \pi(\lambda_{jt}) + \beta(1 - z_t)\mathcal{V}(\lambda_{jt}).
\end{aligned} \tag{C.5}
$$

The intuition behind this form is that innovation and product market activity do not interact from the perspective of the firm and are thus separable from the perspective of the firm. Furthermore, the firms product lines do not interact with each other and, thus, again are separable. □

Lemma C.1. *The growth rate in the economy is given by*

$$
g = \int_0^1 z_{it}(\mathbb{E}[\lambda] - 1)di = z \cdot \mathbb{E}[\ln \lambda] \tag{C.6}
$$

where $z \equiv \int_0^1 z_{it}di$ is the aggregate innovation rate, which is constant along the BGP.

Proof of Lemma C.1.

$$
\begin{aligned}
g = \frac{A_{t+1} - A_t}{A_t} &\approx \ln\left(A_{t+1}/A_t\right) = \int_0^1 \ln\left(A_{jt+1}/A_{jt}\right) dj \\
&= \int_0^1 \left(z_{it} \ln \lambda_{it} + (1 - z_{it}) \ln(1)\right) di = \left(\int_0^1 z_{it} di\right) \mathbb{E}[\ln \lambda_{it}]
\end{aligned}
$$

The approximation holds for low values of g, which is applicable in this case. The second equality simply introduces the definition of A_t. The first equality in the second line follows as each product line has the same probability to be innovated on my a random firm such that the expected improvement is simply the expected improvement made by a random firm. A random firm improves upon a product line by λ_{it}, which is not known in advance, with probability z_{it} and makes no improvement otherwise. Finally, since the improvement size it not known in advance, $\ln \lambda_{it}$ is independent of z_{it}, which leads to the second equality in the second line. □

C.2 Microfounding the Wage Function in GE

The wage function can be motivated in a model where R&D workers have a preference for an even distribution across firms. I will present the static problem below, which can be embedded in infinite horizon straight-forwardly.

$$\begin{aligned}
&\max_{\{\ell_{it}, c_t\}} \quad \log c_t - \frac{L}{1+\xi} \times \left(\int_0^1 \left(\frac{\ell_{it}}{\int_0^1 \ell_{it} di} \right)^{1+\xi} + \tilde{\ell} \times (1+\xi) \times \frac{\ell_{it}}{\int_0^1 \ell_{it} di} di \right) \\
&\text{s.t.} \quad c_t = \int_0^1 \left(\frac{\ell_{it}}{L} \right) W_{it} di \quad \text{and} \quad \int_0^1 \ell_{it} di \leq L
\end{aligned} \tag{C.7}$$

There is a unit mass of inventors, which are hand to mouth in equilibrium. Inventors like consumption, which they finance through wage income. Workers face different wages by across firms, which they take as given, and optimize allocation across firms subject to a disutility for dispersed allocations.

The household problem gives rise to the simple wage function

$$\frac{\ell_{it}}{\int_0^1 \ell_{it} di} = \left(\frac{W_{it}}{W_t} - \bar{\ell} \right), \tag{C.8}$$

where $\bar{\ell} = L\lambda_\ell + \tilde{\ell}$ and $W_t = \int_0^1 \left(\frac{\ell_{it}}{\int_0^1 \ell_{it} di} \right) W_{it} di$ is the average wage. Here λ_ℓ is the Lagrange multiplier on the inventor constraint. Note that the latter will always be binding as labor disutility is independent of total inventor supply, but more employment implies larger consumption.

Firms with relatively high wages receive relatively more workers, but the strength of this mechanism depends on α and ξ. The wage elasticity is given by

$$\frac{\partial \ln W_{it}}{\partial \ln \ell_{it}} = \xi \times \frac{\left(\frac{\ell_{it}}{L}\right)^{\xi}}{\frac{1}{\alpha} - \int_0^1 \left(\frac{\ell_{it}}{L}\right)^{1+\xi} di + \left(\frac{\ell_{it}}{L}\right)^{\xi}}, \tag{C.9}$$

Note that this formulation coincides with the wage function in the main text for $\bar{\ell} = \frac{1}{\alpha} - \int_0^1 \left(\frac{\ell_{it}}{L}\right)^{1+\xi} di$. In this formulation, a lower α performs a similar role to a large $\bar{\ell}$, by flattening the elasticity profile. The formulation in the text reduces the computational burden of solving the model.

C.3 Numerical Solution

I employ two solution algorithms when solving the model, one for moment matching and one for counterfactuals. The first one imposes a growth rate of 1.5% exogenously and sets the average R&D productivity μ accordingly. The second one takes R&D productivity as given and solves for the growth rate of the economy.

Algorithm with exogenous growth rate. The model with fixed growth rate has two features that I will take advantage of. Firstly, I can solve for the equilibrium innovation rate directly using the definition of the growth rate one I've fixed the process for λ

$$z = \frac{g}{\mathbb{E}[\ln \lambda]}.$$

This is useful as it pins down the equilibrium discount rate in the economy without requiring another loop.

Secondly, wages are directly proportional to the aggregate R&D productivity level. Thus, once we have solved for the equilibrium allocation of labor across firms for an arbitrary productivity level with a market clearing wage, we can scale the wage and R&D productivity such that the allocation remains the same, but the economy achieves the required innovation rate z.

My algorithm then involves an inner and an outer loop. In the inner loop I solve for firms' optimal R&D policy and the resulting steady state distribution using standard value function iteration with Howard improvement steps and non-stochastic simulation. In the outer loop, I use a bisection algorithm to determine the equilibrium wage that clears the inventor market for a given average productivity level.

Once the outer loop converged, I calculate the innovation rate under the average R&D productivity level and then scale wages and R&D productivity to achieve the required innovation rate to achieve a growth rate of 1.5% per year. I confirm my guess by solving the model under this parameterization and calculating the model's growth rate.

Algorithm with endogenous growth rate. In the algorithm with endogenous growth rate I instead fix the average R&D level and proceed in three loops. The inner two loops are described above and solve for firms' optimal policy, allocation across states, and R&D wage for a given innovation rate. In the outer loop I then solve for the equilibrium growth rate using bisection. In each step I assume a growth rate, calculate the implied innovation rate and firms' discount rate. After solving the model I then check on the model implied growth rate and iterate until initial guess and model implied growth rate converge.

Simulation. Once I solved the model, I simulate data for a single firm with a number of R&D lines, which coincide in R&D productivity and, thus, in R&D employment. I set the number of R&D lines N such that the simulated data matches the average number of patents in my sample $N_P = 520$:

$$N = \frac{N_P}{z}.$$

In each period, I first determine the firms' optimal R&D policy using the policy function together with the associated R&D success probability. I then draw the number of successful inventions from a Bernoulli distribution using with the R&D success probability and number of R&D lines as parameters. For each of the successful inventions I then draw a step-size from the calibrated geometric distribution and record the implied patent valuation. Finally, I use the Markov process for the R&D productivity process to draw next periods R&D productivity.

I repeat this procedure until I have 100050 periods and discard the first 50 as burn-in. With the remaining data I follow the same steps as in my empirical exercise to calculate the relevant statistics.

C.4 Alternative Calibrations

This section presents results for two additional sets of calibration targets. For both cases, I report the alternative calibration, target moments, and growth implications of monopsony.

Size-based Targets. The first alternative uses the first two estimates in column (3) instead of column (2) of Table 4 as target moments.

Table C.1: Model vs Data Moments

Moment	Data	Model	Target	Source
Average markup	0.200	0.200	λ	Norm.
SD of log patent valuations	0.562	0.562	P	Data
SD of R&D growth	0.316	0.316	σ	Data
Auto-corr. of log R&D	0.922	0.922	ρ	Data
Auto-corr. of R&D growth	-0.017	0.043	ϕ	Data
Avg. wage elasticity	0.963	0.790	$\{\xi, \bar{\ell}\}$	Data
Avg. wage elas. for low inventors	0.410	0.410	ξ	Data
Diff. in avg. wage elas. high vs low inventors	1.245	1.295	$\bar{\ell}$	Data
Inventor - R&D expenditure elas.	0.638	0.578	$\{\xi, \bar{\ell}\}$	Data
Auto-corr. of Return on R&D	0.651	0.403	$\{\xi, \bar{\ell}, \phi\}$	Data

Note: This table reports model and data moments targeted in the calibration the model with monopsony power. Model values based on simulation with 100,000 observations. I estimate the auto-correlations accounting for permanent firm differences as in Han and Phillips (2010). The estimated wage elasticities respond to the estimates in columns (1) and (3) of Table 4. R&D return auto-correlation is calculated at the 5-year horizon.

Table C.2: Calibrated Parameters — Size-based Calibration

Parameter	Description	Value	Source
A. External calibration			
β	Discount factor	0.970	Standard value
γ	R&D scale elasticity	0.500	Acemoglu et al. (2018)
L	Researchers	0.142	Acemoglu et al. (2018)
δ	Inventor turnover	0.120	Natural turnover in LED
B. Internal calibration			
λ	Minimum step size	1.080	Direct
$\bar{P}$	Step size shape parameter	0.447	Direct
σ	Std. dev. R&D prod. shocks	0.476	Moment matching
ρ	Autocorr. R&D prod.	0.860	Moment matching
ϕ	Adjustment cost	0.072	Moment matching
ξ	Avg. inventor elasticity	7.447	Moment matching
$\bar{\ell}$	Rel. inventor elasticity	9.504	Moment matching

Note: Table reports model calibration.

Table C.3: Return Dispersion, Growth, and Monopsony — Size-based Calibration

Model	SD	Growth-rate	Welfare
Baseline	0.43	1.50%	—
No monopsony	0.03	1.57%	2.3%
Common monopsony ($\bar{\ell} = 0$)	0.01	1.59%	3.2%
No preferences ($\xi = 0$)	0.06	1.73%	7.7%

Note: Table reports model results for main calibration and counterfactual where firms take wages as given. SD refers to the standard deviation of log R&D returns based on simulation with 100,000 periods. Welfare column quantifies growth-rate change in terms of consumption equivalent change.

Seegmiller-based Targets. The second alternative replaces my estimates of the inverse inventor supply elasticity with the estimates for high-skilled workers in Seegmiller (2021). In particular, I target the four estimates in the bottom panel of Table 4.

Table C.4: Model vs Data Moments — Seegmiller-based Calibration

Moment	Data	Model	Target	Source
Average markup	0.200	0.200	λ	Norm.
SD of log patent valuations	0.562	0.562	P	Data
SD of R&D growth	0.316	0.316	σ	Data
Auto-corr. of log R&D	0.922	0.921	ρ	Data
Auto-corr. of R&D growth	-0.017	0.023	ϕ	Data
Wage elas Q1	2.042	2.180	$\{\xi, \bar{\ell}\}$	Seegmiller (2021)
Wage elas Q2	1.388	1.372	$\{\xi, \bar{\ell}\}$	Seegmiller (2021)
Wage elas Q3	1.389	1.058	$\{\xi, \bar{\ell}\}$	Seegmiller (2021)
Wage elas Q4	0.735	0.753	$\{\xi, \bar{\ell}\}$	Seegmiller (2021)
Inventor - R&D expenditure elas.	0.638	0.552	$\{\xi, \bar{\ell}\}$	Data
Auto-corr. of Return on R&D	0.651	0.477	$\{\xi, \bar{\ell}, \phi\}$	Data

Note: This table reports model and data moments targeted in the calibration the model with monopsony power. Model values based on simulation with 100,000 observations. I estimate the auto-correlations accounting for permanent firm differences as in Han and Phillips (2010). The estimated wage elasticities respond to the four estimates in the bottom panel of Table 4 in Seegmiller (2021). R&D return auto-correlation is calculated at the 5-year horizon.

Table C.5: Calibrated Parameters — Seegmiller-based Calibration

Parameter	Description	Value	Source
A. External calibration			
β	Discount factor	0.970	Standard value
γ	R&D scale elasticity	0.500	Acemoglu et al. (2018)
L	Researchers	0.142	Acemoglu et al. (2018)
δ	Inventor turnover	0.120	Natural turnover in LED
B. Internal calibration			
λ	Minimum step size	1.080	Direct
$\bar{P}$	Step size shape parameter	0.447	Direct
σ	Std. dev. R&D prod. shocks	0.446	Moment matching
ρ	Autocorr. R&D prod.	0.867	Moment matching
ϕ	Adjustment cost	0.068	Moment matching
ξ	Avg. inventor elasticity	2.531	Moment matching
$\bar{\ell}$	Rel. inventor elasticity	1.902	Moment matching

Note: Table reports model calibration.

Table C.6: Return Dispersion, Growth, and Monopsony — Seegmiller-based Calibration

Model	SD	Growth-rate	Welfare
Baseline	0.17	1.50%	—
No monopsony	0.03	1.53%	1.0%
Common monopsony ($\bar{\ell} = 0$)	0.00	1.54%	1.3%
No preferences ($\xi = 0$)	0.02	1.58%	2.6%

Note: Table reports model results for main calibration and counterfactual where firms take wages as given. SD refers to the standard deviation of log R&D returns based on simulation with 100,000 periods. Welfare column quantifies growth-rate change in terms of consumption equivalent change.

C.5 Perfect Price Discrimination

In this section I consider price discrimination across workers as an alternative perspective on R&D return dispersion. For this purpose, I ignore adjustment cost and work with the resulting static R&D model. Perfect price discrimination can result in R&D return dispersion due to a wedge between marginal and average returns. Firms equalize marginal benefit to unconstrained marginal cost, and, thus, marginal R&D returns are equalized as well, however, average and marginal return are no longer proportional. Thus, while average R&D returns can be still dispersed, it does not imply that resources are misallocated.

Lemma C.2. *Let $F(\ell) = \varphi \cdot \ell^{\gamma}$ and assume that the cost function is given by*

$$C(\ell) = W\left(\int_0^{\ell}\left((1+\xi)\left(\frac{l}{L}\right)^{\xi} + \bar{\ell}\right) dl\right). \tag{C.10}$$

Then, firms take wages as given and set marginal benefit equal to marginal cost. Nonetheless, the Return on R&D is dispersed and given by

$$\frac{F(\ell^*)V}{C(\ell^*)} = \frac{1}{\gamma} \times \left(1 + \xi \times \frac{\left(\frac{\ell^*}{L}\right)^{\xi}}{\left(\frac{\ell^*}{L}\right)^{\xi} + \bar{\ell}}\right). \tag{C.11}$$

Proof. Integrating the cost function, can derive the same cost function as in the main text. Resultingly, first order conditions coincide as does the specification of R&D returns. □

The difference in the models is not only of rhetorical importance, but also determines whether there is a market inefficiency assuming that wages are shaped by preferences. Under perfect price discrimination, firms equalize marginal cost and benefit such that the resulting allocation is efficiency. In contrast, under monopsony, firms equalize marginal benefits to marginal cost adjusted for a markdown reflecting their market power. The resulting allocation is inefficient unless we subsidize firms until marginal benefit and cost are equalized.

This finding raises the question of how we can differentiate between models in the data. The key difference is the price impact on infra-marginal inventors. Under perfect price discrimination, infra-marginal wages are unaffected by labor demand, while they are affected under monopsony. My data does not allow me to directly shed light on this issue, however, Seegmiller (2021) documents wage change for incumbent worker of comparable magnitude to new hires in response to labor demand shocks, which suggests that monopsony power is the empirically relevant case.

D A Result on Return Dispersion and Frictions

In this Appendix, I highlight one approach to quantifying the potential importance of R&D return dispersion in a simple growth model. The results are similar in spirit to Hsieh and Klenow (2009) and are further explored in the companion paper Lehr (2022). The main disadvantage of this approach is that it interprets all variation in R&D returns as frictions.

Theory. A unit mass of firms innovates with probability z_{it} each period, depending on their R&D efficiency φ_{it} and inventors hired ℓ_{it} via a decreasing returns to scale production function with scale elasticity $\frac{1}{1+\phi}$:

$$z_{it} = \varphi_{it} \ell_{it}^{\frac{1}{1+\phi}}.$$

Firms value innovation at expected value $\mathcal{V}_{it}$ and face common wage W_t. Input choices are distorted by exogenous wedge Δ_{it} such that their optimal inventor employment solves:

$$\frac{\partial z_{it}}{\partial \ell_{it}} \mathcal{V}_{it} = (1 + \Delta_{it}) \times W_t.$$

The wage W_t is determined via labor market clearing with mass of R&D workers $\mathcal{L}$:

$$\mathcal{L} = \int_0^1 \ell_{it} di.$$

Finally, the economic growth rate depends on innovation rates z_{it} and the growth impact of innovations $\lambda_{it} - 1$:

$$g_t = \int_0^1 z_{it}(\lambda_{it} - 1) di.$$

Proposition D.1. *Let the ratio of productivity impact to valuation be constant across firms, i.e. $V_{it} \propto \lambda_{it}$, and define a firm's R&D productivity as $\gamma_{it} \equiv \varphi_{it} \mathcal{V}_{it}$. We can express the economic growth-rate as the product of two factors:*

$$g_t = \tilde{g}_t \times \Xi_t. \tag{D.1}$$

The term $\tilde{g}_t$ captures the growth rate under the growth maximizing R&D worker allocation and is given by

$$\tilde{g}_t = \mathcal{L}^{\frac{1}{1+\phi}} \times \left(\int_0^1 \gamma_{it}^{\frac{1+\phi}{\phi}} di \right)^{\frac{\phi}{1+\phi}}. \tag{D.2}$$

The term Ξ_t captures the growth cost induced by frictions and can be interpreted as the *fraction of potential growth that is truly realized:*

$$\Xi_t = \frac{\int_0^1 \omega_{it}(1+\Delta_{it})^{-\frac{1}{\phi}} di}{\left(\int_0^1 \omega_{it}(1+\Delta_{it})^{-\frac{1+\phi}{\phi}} di\right)^{\frac{1}{1+\phi}}} \quad \textit{with} \quad \omega_{it} \equiv \frac{\gamma_{it}^{\frac{1+\phi}{\phi}}}{\int_0^1 \gamma_{it}^{\frac{1+\phi}{\phi}} di}. \tag{D.3}$$

Note that $\Xi_t \in (0,1]$ and $\Xi_t = 1$ if $\Delta_{it} = \Delta_t$.

Proof. The formulas follow by rearranging terms and solving for the growth rate. $\Xi_t \in (0,1]$ follows from Jensen's inequality since the denominator is a concave transformation of the nominator. □

Measurement. The proposition allows us to quantify the impact of R&D return dispersion within a basic endogenous growth framework. To estimate Ξ_t, we need three ingredients. Firstly, we need to fix ϕ and, as in the main text, I will set $\phi = 1$. Secondly, we need to measure Δ_{it}, which we can read off the return on R&D:

$$\text{R\&D Return}_{it} \equiv \frac{z_{it}\mathcal{V}_{it}}{W_t \ell_{it}} = (1+\phi) \times \Delta_{it}. \tag{D.4}$$

Note that the factor $1+\phi$ does not affect the calculations as the formula for Ξ_t is homogeneous of degree 0 in the scale of $1+\Delta_{it}$ and γ_{it}. This result is due to assuming a constant mass of R&D workers, such that heterogeneity in return and productivity only affects the allocation of R&D resources across firms. Finally, we need to measure R&D productivity. Rearranging firm order conditions, one can show that

$$\gamma_{it} \propto (1+\Delta_{it}) \times (W_t \ell_{it})^{\frac{\phi}{1+\phi}}, \tag{D.5}$$

which is sufficient to pin down relative productivity, and, thus, sufficient to construct Ξ_t.

Results. We thus have all the requirement ingredients and can implement the formulas. Column(1) in Table D.1 reports the results. Without adjustments, the model estimates an aggregate R&D allocation efficiency around 60%. Taken at face value, the estimate implies that the growth rate would be $1/0.6 - 1 = 67\%$ larger. Once we make the measurement adjustment lined out in Section 3, our estimate increase to 70% efficiency, implying a potential gain from reducing Return on R&D dispersion around 40%. Against a baseline growth rate of 1.5%, these estimates suggest a potential gain of 1 and 0.6 p.p. annual growth.

Table D.1: Allocative Efficiency Estimates

Return on R&D	Main	Measurement Error	
		15%	30%
Baseline	60.2%	69.2%	78.1%
Adjusted	71.7%	78.5%	84.8%

Note: Estimates following Proposition D.1 assuming $\phi = 1$. Measurement error adjustments shrink log R&D by 1 minus adjustment fraction.

For comparison, Hsieh and Klenow (2009) estimate that US productivity, and thus production, could be 40% larger without dispersion in the total revenue productivity, which is conceptually similar to R&D returns. Similarly, Berger et al. (2022) estimate that US output could be 21% larger in absence of monopsony power. My estimates are on the same order of magnitude, however, they concern the growth rate and not productivity level. This difference has important welfare implications as welfare tends to be more sensitive to productivity growth rather than level due to its cumulative nature.

Discussion. One caveat with this approach is that we have to interpret all variation in the R&D returns as being driven by Δ_{it}. For example, measurement error raises R&D return dispersion, which in turn mechanically leads to lower estimates of Ξ_t. I highlight this challenge in column (2) and (3) in Table D.1, where I assume that measurement error constitutes 15% and 30% of the variation respectively. Mechanically, this assumption pushes up the estimated R&D allocation efficiency. Another approach to dealing with measurement error is to focus on changes over time. I explore this in detail in Lehr (2022) and find that indeed the dispersion in R&D returns has risen since 1975. Through the lens of the model, this suggest that misallocation has worsened, potentially contributing to the growth slowdown documented in Syverson (2017).

E Top 50 and Bottom 50 Firms by Return on R&D

Table E.1: Top and Bottom Companies by average Return on R&D

Rank	Company Name	Avg. ln Return on R&D
1	BJ SERVICES CO	3.88
2	INTUITIVE SURGICAL INC	3.76
3	AT&T INC	3.68
4	CAMERON INTERNATIONAL CORP	3.55
5	ILLINOIS TOOL WORKS	3.45
6	SALESFORCE.COM INC	3.42
7	WEATHERFORD INTL PLC	3.38
8	CREE INC	3.33
9	ARCHER-DANIELS-MIDLAND CO	3.33
10	INTL PAPER CO	3.32
11	MOBIL CORP	3.22
12	HALLIBURTON CO	3.22
13	UNOCAL CORP	3.20
14	DELL TECHNOLOGIES INC	3.19
15	CONOCOPHILLIPS	3.18
16	EXXON MOBIL CORP	3.16
17	ALIGN TECHNOLOGY INC	3.16
18	DEXCOM INC	3.14
19	BAKER HUGHES INC	3.14
20	QUALCOMM INC	3.13
21	OCCIDENTAL PETROLEUM CORP	2.99
22	ALZA CORP	2.98
23	TEXACO INC	2.96
24	ATLANTIC RICHFIELD CO	2.95
25	CHEVRON CORP	2.95

Note: This table reports the company names of firms with the best and worst average ln Return on R&D in the sample. I restrict the list to firms with at least 10 observations. See Section 3 for details on the data construction.

Table E.2: Top and Bottom Companies by average Return on R&D (continued)

Rank	Company Name	Avg. ln Return on R&D
26	BLACKBERRY LTD	2.95
27	AMOCO CORP	2.95
28	LINDSAY CORP	2.95
29	RED HAT INC	2.94
30	U S SURGICAL CORP	2.94
31	RESMED INC	2.91
32	AKAMAI TECHNOLOGIES INC	2.89
33	STANDARD OIL CO	2.89
34	ALTERA CORP	2.88
35	MICRON TECHNOLOGY INC	2.87
36	UNIVERSAL DISPLAY CORP	2.87
37	SUNPOWER CORP	2.85
38	FORTINET INC	2.84
39	SYMBOL TECHNOLOGIES	2.83
40	BEAM INC	2.83
41	ECOLAB INC	2.81
42	BROADCOM INC	2.81
43	COOPER INDUSTRIES PLC	2.79
44	ALPHABET INC	2.79
45	SANDISK CORP	2.77
46	WEST PHARMACEUTICAL SVSC INC	2.74
47	APPLE INC	2.74
48	ACUITY BRANDS INC	2.73
49	DIGIMARC CORP	2.73
50	KERR-MCGEE CORP	2.72

Note: This table reports the company names of firms with the best and worst average ln Return on R&D in the sample. I restrict the list to firms with at least 10 observations. See Section 3 for details on the data construction.

Table E.3: Top and Bottom Companies by average Return on R&D (continued)

Rank	Company Name	Avg. ln Return on R&D
419	AEROQUIP-VICKERS INC	0.67
420	AEROJET ROCKETDYNE HOLDINGS	0.67
421	SILICON GRAPHICS INC	0.66
422	AMERICAN AXLE & MFG HOLDINGS	0.65
423	COHERENT INC	0.65
424	AVID TECHNOLOGY INC	0.65
425	ITRON INC	0.65
426	TELLABS INC	0.64
427	GOULD INC	0.63
428	MILACRON INC	0.60
429	RIGEL PHARMACEUTICALS INC	0.57
430	BECKMAN COULTER INC	0.55
431	MAXYGEN INC	0.55
432	HASBRO INC	0.54
433	MICROVISION INC	0.53
434	FIRESTONE TIRE & RUBBER CO	0.52
435	APPLIED MICRO CIRCUITS CORP	0.51
436	MODINE MANUFACTURING CO	0.48
437	FORD MOTOR CO	0.46
438	DIGITAL EQUIPMENT	0.46
439	CELANESE CORP-OLD	0.46
440	SCOTT TECHNOLOGIES INC	0.45
441	AXCELIS TECHNOLOGIES INC	0.42
442	ANALOGIC CORP	0.41
443	QUANTUM CORP	0.40

Note: This table reports the company names of firms with the best and worst average ln Return on R&D in the sample. I restrict the list to firms with at least 10 observations. See Section 3 for details on the data construction.

Table E.4: Top and Bottom Companies by average Return on R&D (continued)

Rank	Company Name	Avg. ln Return on R&D
444	AMDOCS	0.39
445	DATA GENERAL CORP	0.39
446	SPERRY CORP	0.37
447	ELECTRO SCIENTIFIC INDS INC	0.35
448	NAVISTAR INTERNATIONAL CORP	0.31
449	MAXTOR CORP	0.30
450	QLOGIC CORP	0.29
451	MCDONNELL DOUGLAS CORP	0.29
452	TANDEM COMPUTERS INC	0.29
453	TELECOMMUNICATION SYS INC	0.24
454	ROBINS (A.H.) CO	0.23
455	SPANSION INC	0.17
456	ELECTRONICS FOR IMAGING INC	0.15
457	EXTREME NETWORKS INC	0.13
458	WANG LABS INC	0.09
459	BIO-RAD LABORATORIES INC	0.08
460	DAY INTERNATIONAL INC	0.08
461	ROGERS CORP	-0.08
462	SMITH (A.O.)	-0.09
463	GENERAL MOTORS CO	-0.14
464	AMDAHL CORP	-0.30
465	VISTEON CORP	-0.34
466	MENTOR GRAPHICS CORP	-0.35
467	DE SOTO INC	-0.37
468	DONNELLY CORP	-0.40

Note: This table reports the company names of firms with the best and worst average ln Return on R&D in the sample. I restrict the list to firms with at least 10 observations. See Section 3 for details on the data construction.

Table E.5: Top and Bottom Companies by average adjusted Return on R&D

Rank	Company Name	Avg. ln Return on R&D
1	INTUITIVE SURGICAL INC	3.82
2	DEXCOM INC	3.64
3	DIGIMARC CORP	3.58
4	ILLINOIS TOOL WORKS	3.53
5	CREE INC	3.52
6	BROADCOM INC	3.51
7	SALESFORCE.COM INC	3.47
8	FORTINET INC	3.45
9	AT&T INC	3.34
10	QUALCOMM INC	3.34
11	GENTEX CORP	3.20
12	MICRON TECHNOLOGY INC	3.17
13	ECOLAB INC	3.17
14	F5 NETWORKS INC	3.16
15	SUNPOWER CORP	3.14
16	UNIVERSAL DISPLAY CORP	3.14
17	RED HAT INC	3.12
18	RESMED INC	3.12
19	ILLUMINA INC	3.11
20	CAMERON INTERNATIONAL CORP	3.06
21	MICROSOFT CORP	3.02
22	BLACKBERRY LTD	2.96
23	ALTERA CORP	2.95
24	AIR PRODUCTS & CHEMICALS INC	2.94
25	DELL TECHNOLOGIES INC	2.91

Note: This table reports the company names of firms with the best and worst average ln Return on R&D in the sample. I restrict the list to firms with at least 10 observations. Adjustments include (1) winsorizing patent valuations, (2) knowledge capital, (3) NAICS3$\times$ Year effects, (4) amenities, and (5) acquisitions. See Section 3 and B.1 for details.

Table E.6: Top and Bottom Companies by average adjusted Return on R&D (continued)

Rank	Company Name	Avg. ln Return on R&D
26	LINDSAY CORP	2.91
27	MASIMO CORP	2.88
28	ALZA CORP	2.88
29	APPLE INC	2.86
30	SANDISK CORP	2.86
31	VIASAT INC	2.82
32	FUELCELL ENERGY INC	2.81
33	ALIGN TECHNOLOGY INC	2.81
34	NVIDIA CORP	2.80
35	VMWARE INC -CL A	2.80
36	XILINX INC	2.79
37	SYMBOL TECHNOLOGIES	2.79
38	ALCOA INC	2.78
39	WATERS CORP	2.74
40	NETLOGIC MICROSYSTEMS INC	2.70
41	LIFE TECHNOLOGIES CORP	2.69
42	PITNEY BOWES INC	2.65
43	CORNING INC	2.60
44	U S SURGICAL CORP	2.59
45	AMKOR TECHNOLOGY INC	2.56
46	VERTEX PHARMACEUTICALS INC	2.54
47	LINEAR TECHNOLOGY CORP	2.54
48	PROCTER & GAMBLE CO	2.54
49	AKAMAI TECHNOLOGIES INC	2.53
50	COLGATE-PALMOLIVE CO	2.52

Note: This table reports the company names of firms with the best and worst average ln Return on R&D in the sample. I restrict the list to firms with at least 10 observations. Adjustments include (1) winsorizing patent valuations, (2) knowledge capital, (3) NAICS3$\times$ Year effects, (4) amenities, and (5) acquisitions. See Section 3 and B.1 for details.

Table E.7: Top and Bottom Companies by average adjusted Return on R&D (continued)

Rank	Company Name	Avg. ln Return on R&D
419	AGCO CORP	0.88
420	TORO CO	0.86
421	CORDIS CORP	0.86
422	FORD MOTOR CO	0.83
423	TANDEM COMPUTERS INC	0.82
424	MILACRON INC	0.81
425	VEECO INSTRUMENTS INC	0.81
426	DENNISON MFG CO	0.78
427	MERITOR INC	0.77
428	MAXYGEN INC	0.76
429	INTERMEC INC	0.76
430	RIGEL PHARMACEUTICALS INC	0.75
431	SURGALIGN HOLDINGS INC	0.73
432	ACTEL CORP	0.72
433	ELECTRO SCIENTIFIC INDS INC	0.71
434	APPLIED MICRO CIRCUITS CORP	0.70
435	G-I HOLDINGS INC	0.70
436	CA INC	0.69
437	MODINE MANUFACTURING CO	0.69
438	COHERENT INC	0.68
439	MICROSTRATEGY INC	0.67
440	QLOGIC CORP	0.67
441	TELLABS INC	0.62
442	ZENITH ELECTRONICS CORP	0.60
443	MENTOR GRAPHICS CORP	0.60

Note: This table reports the company names of firms with the best and worst average ln Return on R&D in the sample. I restrict the list to firms with at least 10 observations. Adjustments include (1) winsorizing patent valuations, (2) knowledge capital, (3) NAICS3$\times$ Year effects, (4) amenities, and (5) acquisitions. See Section 3 and B.1 for details.

Table E.8: Top and Bottom Companies by average adjusted Return on R&D (continued)

Rank	Company Name	Avg. ln Return on R&D
444	QUANTUM CORP	0.55
445	AVID TECHNOLOGY INC	0.55
446	CELANESE CORP-OLD	0.53
447	NAVISTAR INTERNATIONAL CORP	0.50
448	BECKMAN COULTER INC	0.50
449	LUBRIZOL CORP	0.49
450	CONEXANT SYSTEMS INC	0.46
451	AMDAHL CORP	0.41
452	SPANSION INC	0.41
453	ROGERS CORP	0.39
454	EXTREME NETWORKS INC	0.36
455	ANALOGIC CORP	0.35
456	MAXTOR CORP	0.33
457	DONNELLY CORP	0.33
458	GENERAL MOTORS CO	0.24
459	AXCELIS TECHNOLOGIES INC	0.21
460	ROBINS (A.H.) CO	0.20
461	ELECTRONICS FOR IMAGING INC	0.20
462	STEEL EXCEL INC	0.17
463	HASBRO INC	-0.03
464	BIO-RAD LABORATORIES INC	-0.06
465	AT&T CORP	-0.09
466	DE SOTO INC	-0.20
467	VISTEON CORP	-0.23
468	SMITH (A.O.)	-0.27

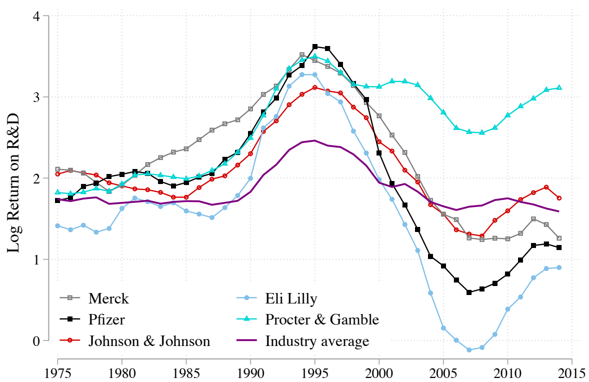
Note: This table reports the company names of firms with the best and worst average ln Return on R&D in the sample. I restrict the list to firms with at least 10 observations. Adjustments include (1) winsorizing patent valuations, (2) knowledge capital, (3) NAICS3× Year effects, (4) amenities, and (5) acquisitions. See Section 3 and B.1 for details.

F Case Studies

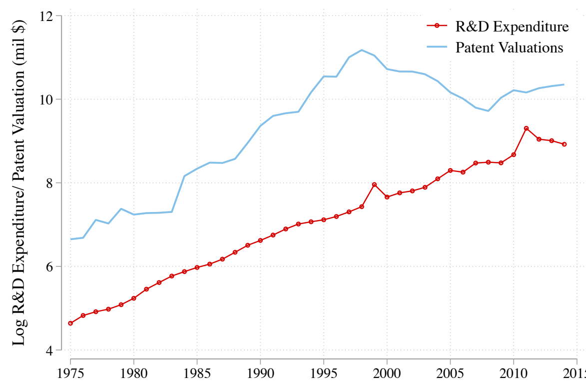
In this section I highlight selected case studies that provide further context on the dynamics and origin of R&D return dispersion. The first case study focuses on Merck and the Pharma industry, shedding a light on some of the most innovative firms in the economy in an industry where patent rights are key to guarding innovation from competitors. The second case study takes a look at the natural resource industry, which, perhaps surprisingly, has earned larger R&D returns than any other industry.

F.1 Merck & the Pharma Industry

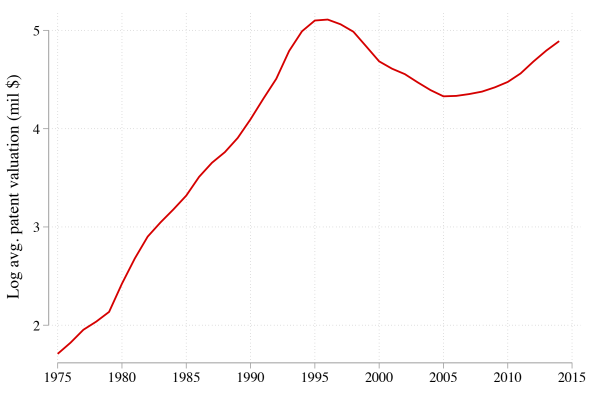
Figure F.1: Merck's R&D Performance 1975-2014



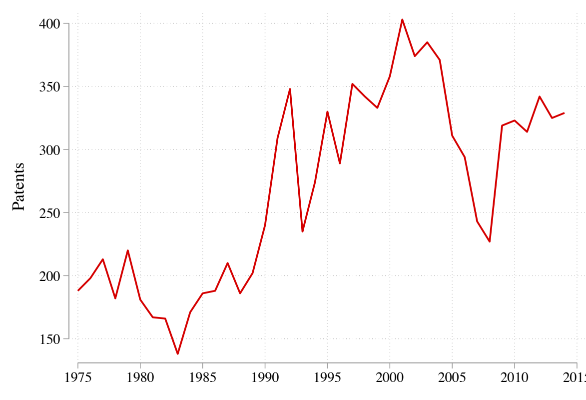
(a) Return on R&D



(b) R&D Expenditure & Patent Valuations



(c) Average Patent Valuation



(d) Patents

Notes: Panel (a) plots the 5-year return on R&D for selected firms within chemical manufacturing (NAICS 325) as well as an industry average for firms with at least 20 active years within the sample. Panel (b)-(d) focus on Merck & Co only. Panel (b) plots annual R&D expenditure and patent valuations. Panel (c) plots the average patent valuation at the 5-year level. Panel (d) plots the annual Cnumber of patents.

Panel (a) in Figure F.1 plots the evolution of R&D returns for Merck, important competitors, and the industry average. R&D returns are relatively constant until the late 1980s, where they begin to rise. Returns peak around 1995 and, for all but Proctor & Gamble, subsequently return to their previous level or lower. R&D returns are notably more dispersed post 2005 than in previous decades.

Panels (b)-(d) take a closer look at Merck in particular. In Panel (b) I plot the two components of R&D returns, patent valuations and R&D expenditure, separately. The emerging pattern is one of an essentially constant growth rate of R&D expenditure over the entire sample, while patent valuation drive fluctuations in R&D returns by first accelerating in the early parts of the same and subsequently declining below their initial trend. Panels (c) and (d) reveals that the evolution of patent valuation is driven both by rising patent valuations as well as rising patent counts. Annual patenting is centered around 175 for the 1975 to 1990 period before jumping to a new average level around 300. Patent valuation grow smoothly from 1975 to 1995 and subsequently stabilize.

The emerging patterns suggest that the evolution of R&D returns for Merck is driven partly by a failure to respond to rising innovation output by increasing R&D expenditure and vice versa. Given the year-to-year stability in returns, it appears unlikely that this is driven by perceived uncertainty around the value of innovation. The stability of R&D expenditure across years further raises the question as to the underlying decision making process and, potentially, highlights the importance of adjustment cost, e.g. due to the scarcity of talent, in the R&D process.

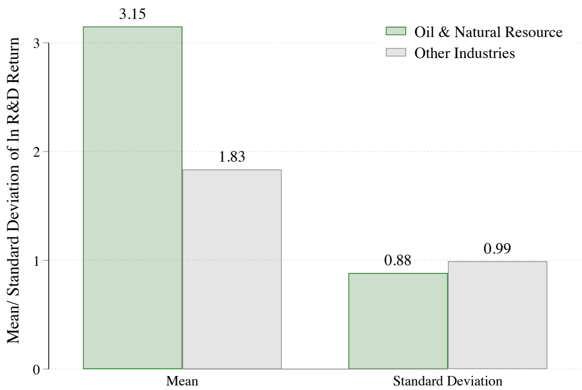
F.2 Exxon and the Natural Resource Industry

Another interesting case is the natural resource industry. As show in Panel (a) in Figure F.2, the average firm in the industry earns a significantly higher return than firms in other industries, however, the dispersion within the industry is slightly lower than outside the industry.

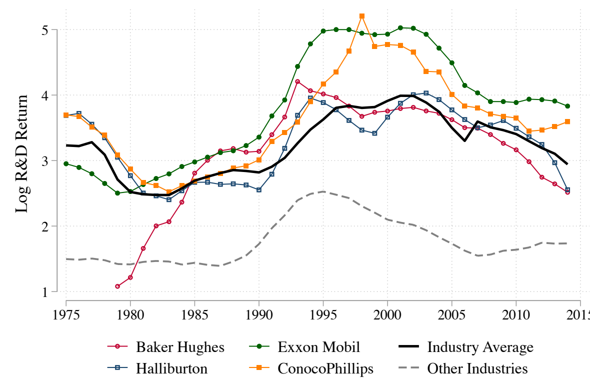
Panel (b) plots the evolution of R&D returns for selected firms in the industry, the industry average, and the average of firms outside the industry. Returns are initially stable until 1990 and subsequently peak around 2000 before returning to pre-peak levels around 2005. Interestingly, the ranking of R&D returns across the four competitors shown is very stable across years with Exxon Mobil earning the highest returns in most years.

Panels (c) and (d) take a closer look at Exxon. Panel (d) plots the evolution of R&D expenditure and patent valuations. The figure reveals very stable R&D expenditure and patent valuation however at different growth rates. Furthermore, patent valuations experience a temporary peak around the 2000s, however, the peak is much stronger for Exxon Mobil and ConocoPhillips than for their competitors.

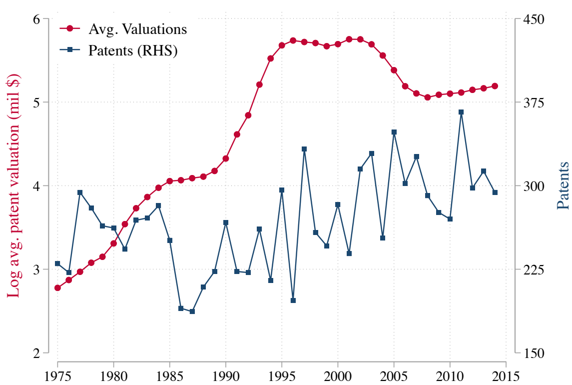
Figure F.2: Exxon's R&D Performance 1975-2014



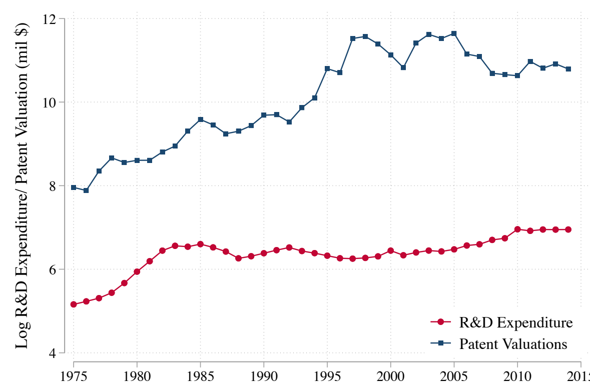
(a) Summary Statistics



(b) R&D Returns



(c) Patents & Their Valuation



(d) R&D Expenditure & Patent Valuations

Notes: Panel (a) plots the average return and standard deviation thereof within the industry and outside of the industry. Panel (b) plots the 5-year return on R&D for selected firms within natural resource industry (NAICS 211,213, and 324) as well as an industry average for firms with at least 20 active years within the sample. Panel (c)-(d) focus on Exxon Mobile only. Panel (d) plots annual R&D expenditure and patent valuations. Panel (c) plots the average patent valuation at the 5-year level and annual patents. Panel (d) plots the annual number of patents.