Does Monopsony Matter for Innovation?*

[PRELIMINARY AND INCOMPLETE]

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Abstract

This paper studies the impact of firms' market power over inventors on U.S. innovation and economic growth. When firms have market power in labor markets, a situation typically referred to as monopsony, they can depress wages by hiring fewer workers. I show that monopsony in the market for inventors can slow down economic growth by depressing the aggregate demand for inventors and by allocating the employed inventors inefficiently. Misallocation occurs as larger firms depress their hiring of inventors disproportionally because their size makes them more effective at depressing wages. Motivated by this theoretical result, I estimate the firm-level elasticity of inventor employment with respect to their wages, or the inventor labor supply elasticity, using an instrumental variable strategy. My estimates suggest that firms face less than perfectly elastic supply and that this elasticity is lower for firms with an already large inventor workforce. Thus, firms appear to have monopsony power and it is stronger for larger employers. I use this evidence to calibrate a heterogeneous firms endogenous growth model with size-dependent monopsony power. The calibrated model suggests that monopsony power depresses the annual economic growth rate in the U.S. by 0.26 percentage points or 15% and, resultingly, welfare by 6%.

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1 Introduction

Economic activity has become increasingly concentrated among large firms in the U.S.[1] The top 1% of corporate firms accounted for about 80% of revenue in 2020, up from 60% in 1960 (Kwon et al., 2023). Politicians, commentators, and academics alike have raised concerns that rising concentration may be closely linked to a perceived decline in competition.[2] Evidence for such a trend can be found, e.g., in profit rates for U.S.–listed firms, which have risen from less than 1% in 1980 to close to 8% in 2010 (Loecker et al., 2020).

Concerns about insufficient competition increasingly include the power that large firms might have to suppress the wages of their employees, commonly referred to as monopsony power.[3] While monopsony was typically considered most prevalent for "low-skilled" workers in rural communities, e.g., for miners in towns with only few coal mines in close proximity, a growing body of evidence suggests that it is also prevalent for "high-skilled" workers (Goolsbee and Syverson, 2023; Seegmiller, 2023). One interpretation of these novel findings focuses on a perhaps previously less emphasized source of monopsony power: human capital specificity. For example, registered nurses provide invaluable services to hospitals, but their significant human capital—as indicated by the required graduate degree—is only valuable within the profession. Resultingly, hospitals can suppress nurses' compensation in face of limited competition for their services (Prager and Schmitt, 2021).

In this paper, I study the macroeconomic consequences of monopsony power over inventors. Monopsony power over this type of high-skilled labor may be both particularly concerning and prevalent, since the output of inventors, i.e., inventions, is considered one of the key drivers of long-run economic growth and welfare, and their skills tend to be highly specialized. Indeed, anecdotal evidence suggests that Tech companies are aware of their potential market power over these workers and colluded to suppress their wages in the past. For example, large Tech firms had agreements not to poach each others' engineers in order to keep their wages low (Edwards, 2014). Apple, Adobe, Intel, and Google were fined by the Department of Justice in 2010 for these non-poaching agreements, while Microsoft only recently announced that it would not enforce non-compete agreements (of Justice, 2010; Reuters, 2022). Similar cases have emerged in other industries (Kass et al., 2022).

[1]Rising concentration at the national level was first documented by Autor et al. (2020). There is an ongoing debate on the origins and impact thereof (Grullon et al., 2019; Rossi-Hansberg et al., 2019; Berger et al., 2022).

[2]Concerns about rising concentration and declining competition are raised, e.g., in Wu (2018); Philippon (2019); Meagher (2020) and Klobuchar (2021).

[3]For example, labor markets are explicitly mentioned in the White House's 2021 executive order on "Promoting Competition in the American Economy." (House, 2021)

This paper estimates that monopsony power in the market for corporate inventors has a sizable negative impact on innovation and economic growth. Empirically, I find that especially firms with large inventor workforce appear to have significant monopsony power, while smaller firms face more competitive conditions. Interpreted through the lens of a quantitative endogenous growth model, this evidence suggests that monopsony power might depress aggregate inventor employment and lead to an inefficient allocation of inventors across firms. Misallocation occurs through a size-dependent monopsony channel that reduces inventor employment disproportionally for larger employers. Quantitatively, I find that monopsony power over inventors reduces long-run economic growth by 0.26 p.p. leading to welfare loss of 6% compared to a world in which firms act as price takers.

I reach these conclusion in three steps. First, I introduce monopsony power over inventors into an endogenous growth model with heterogeneous firms. Inventors choose their employer based on idiosyncratic preference shocks and wages offered as in Card et al. (2018). Resultingly, firms face an upwards sloping labor supply curve and can lower wages marginally without loosing their entire inventor workforce, as would be the case in the standard competitive model. Similar to Berger et al. (2022), I allow for size-dependent monopsony power such that large employers of corporate inventors may have more power over them. Monopsony power depresses the aggregate demand for corporate inventors, resulting in lower R&D employment—as long as their aggregate supply is not perfectly inelastic—and, therefore, lower economic growth. Size-dependence of monopsony power further induces misallocation across firms as larger firms depress their demand for corporate inventors more than smaller firms, which leads to an additional drag on innovation and economic growth.

In the second step, I present novel evidence on firms' monopsony power over corporate inventors in the U.S. I estimate the average firm-level elasticity of inventor wages with respect to their employment, i.e., their inverse labor supply elasticity, in a sample of U.S.-listed firms by regressing inventor wage growth on employment growth. I construct inventor employment and their wages by combining firms' financial statements with their patent records. The literature has long recognized the potential identification challenges in this setup (Manning, 2011). Most importantly, labor supply shocks, such as preference shocks over firms, can lead to a downwards bias in the estimated elasticity. In particular, a positive labor supply shock reduces the wage a firm needs to pay in order to maintain a given level of employment, which is informative about the wage level of a firm, but not its local labor supply elasticity. I propose to address this identification challenge by using stock market returns as an instrument for shocks to firms' labor demand as in Seegmiller (2023). The instrument is relevant if stock market returns partly reflect shocks that induce the firm to expand, such as demand shocks for its products. It satisfies the exclusion restriction if there is no link between stock market returns and inventor wages other than their employment.

My estimates suggests that monopsony power is both sizable and size-dependent. I estimate an average inverse labor supply elasticity of 0.96, which implies that a firm would lose about 10.3% of its inventors if it were to reduce their wages by 10%. For comparison, Seegmiller (2023) estimates an elasticity of 0.82 for high-skilled workers, while Yeh et al. (2022) estimate an average elasticity of 0.68 for nonproduction workers and Berger et al. (2022) estimate an elasticity of 0.33 for all workers in firms with a 10% market share in the local labor market. Importantly, I find that firms with above median R&D workforce face a larger inverse labor supply elasticity of 1.7 compared to 0.4 for smaller firms. Thus, firms with above median inventor employment would lose only about 6.0% of their R&D workforce if they were to reduce their wages by 10%, while below median R&D employment firm would lose 24.4%. Similarly, Yeh et al. (2022), Berger et al. (2022), and Seegmiller (2023) find that larger employers face less elastic labor supply and, thus, have more monopsony power. For example, Seegmiller (2023) estimates that high-skilled workers in below median size firms have an inverse labor supply elasticity of 0.58 compared to an elasticity of 0.94 for above median sized firms. I confirm that my estimates are not driven by a changing composition of corporate researcher quality nor pre-trends.

In the final step, I extend the model introduced in the first step along several dimensions and calibrate it using the evidence on the labor supply elasticity of inventors. The calibrated model can then be used as a laboratory to study the impact of monopsony for in the market for corporate inventors on innovation and economic growth. I introduce three extensions. First, I allow for non-listed firms in the R&D sector. These firms tend to be much smaller in the data and, thus, may mitigate some of the monopsony power of larger firms. Second, I account for stock-based compensation of inventors, which may constitute a violation of the exclusion restriction in my estimation by providing a direct link between wages and the stock market performance of a firm. Lastly, I allow for non-labor inputs into the R&D production process, which limit the incentives of firms to downsize by providing a substitute for inventors. I calibrate the extended model using a combination of external calibration with standard parameters and moment matching. The calibrated model matches key data moments including the inventor labor supply elasticity estimates.

The calibrated model suggests that monopsony power over inventors slows down innovation and economic growth significantly due to a combination of insufficient R&D employment and misallocation of inventors across firms. Forcing firms to be price takers in the market for inventors increases economic growth from 1.50% to 1.76% per year—a 6% welfare improvement. The acceleration in economic growth is driven both by a 13% rise in R&D employment as well as a significant improvement in aggregate R&D productivity due to more productive allocation of inventors. Holding R&D employment fixed, the improvement in the allocation of inventors alone accelerates economic growth rate by 15 p.p., highlighting the importance of the misallocation channel of size-dependent monopsony. I conclude by highlighting three forces that might limit the cost of monopsony: wage discrimination among workers, firm entry, and the presence of socially inefficient differences in firms' ability to benefit from their inventions.

Literature. This paper is closely connected to three strands of the literature. First, I contribute to the literature on monopsony power by providing novel evidence thereof in the market of corporate inventors and documenting that monopsony power appears to be increasing with firms' inventor employment. The literature documents that monopsony power is pervasive in the production sector and stronger for larger employers (Azar et al., 2020; Arnold, 2021; Kroft et al., 2021; Lamadon et al., 2022; Yeh et al., 2022). Furthermore, there is growing evidence of monopsony power in labor markets for "high-skilled" workers (Prager and Schmitt, 2021; Goolsbee and Syverson, 2023; Seegmiller, 2023). I complement this literature by documenting monopsony power over an important group of skilled workers: corporate inventors. My model builds on the literature microfounding monopsony power via preferences over employers (Card et al., 2018). An alternative approach focuses on a lack of outside options for workers as a microfoundation of monopsony power (Shi, 2023; Schubert et al., 2023; Bagga, 2023). I complement the theoretical literature by introducing preference-based monopsony power into a general equilibrium endogenous growth model with heterogeneous firms. Relatedly, Berger et al. (2022) introduce a structural general equilibrium model of the production with monopsony power.

Second, I contribute to the literature on resource allocation in the R&D sector. The existing literature focuses primarily on the misalignment of private and public marginal benefits of R&D investment, which can also lead to misallocation, rather than misalignment of marginal costs as in my case. The literature has highlighted a range of potential mechanisms for such misalignment including knowledge and business stealing externalities, and differences in firms' ability to profit from their inventions or protect their intellectual property. Romer (1990) and Aghion and Howitt (1992) first argued that this misalignment can lead to under investment in R&D, while the more recent literature is focused on heterogeneous misalignment across firms that leads to misallocation of R&D resources (Acemoglu et al., 2018; Cavenaile et al., 2021; Mezzanotti, 2021; Aghion et al., 2023; König et al., 2022; Terry, 2023). I complement this literature by instead focusing on a misalignment in the marginal costs perceived by the firm and a planner due to monopsony power.[4] Interestingly, this mechanisms leads to the conclusion that large firms might not do enough R&D relative to small firms, while the literature typically finds that they might do too much (Akcigit et al., 2022; Manera, 2022; de Ridder, 2023). These findings suggests that both types of mechanisms might partly offset each other in practice. My paper is also related to the literature on talent (mis-)allocation in the R&D sector (Akcigit et al., 2020; Prato, 2022; Celik, 2023). I complement this literature by focusing on market power as a source of talent misallocation.

Finally, my paper falls within the larger literature on the macroeconomic implications of factor misallocation, which has mostly focused on the production sector. Restuccia and Rogerson (2008) and Hsieh and Klenow (2009) first argued that misallocation of production factors may be significant and could have a large impact on productivity and output. The subsequent literature investigated a range of potential sources of misallocation including financial frictions, government intervention, information frictions, and adjustment costs (Asker et al., 2014; Midrigan and Xu, 2014; David et al., 2016, 2022). More recently, the literature has (re-)considered market power in product and labor markets as a significant source of resource misallocation in the production sector that may significantly reduce aggregate productivity and depress output levels (Loecker et al., 2020; Berger et al., 2022). I contribute to this literature by focusing on misallocation in the R&D sector, which may lead to slower innovation and economic growth rather than lower output levels. This focus coincides with Lehr (2023), who studies misallocation in the R&D sector in general. This paper is complementary as it studies and provides evidence for a particular mechanism of misallocation in the R&D sector: monopsony power.

Organization. The remainder of this paper is structured as follows: Section 2 introduces a heterogeneous firms model with size-dependent monopsony power and derives the key implications thereof for economic growth. Section 3 provides empirical evidence of monopsony power in the market for inventors. Section 4 extends the model, calibrates it to match the empirical evidence, and presents counterfactuals. Section 5 discusses additional factors and Section 6 concludes.

[4] A focus on marginal cost differences also coincides with the larger literature on the impact of financial frictions on R&D investment (Brown et al., 2009; Howell, 2017; Ewens et al., 2022).

2 A Growth Model with Monopsony over Inventors

This section introduces preference-based monopsony power as in Card et al. (2018) into a general equilibrium growth model in the tradition of Romer (1990) to investigate the potential impact of monopsony power on innovation and economic growth. Preference-based monopsony builds on the idea that firms are imperfect substitutes from the perspective of a worker due to e.g. differential amenities, management styles, company cultures or visions. Resultingly, firms face an upwards sloping labor supply curve starting with workers who have a preference for the firm, and thus willing to work at low wages, up to workers having a preference against the firms, and thus requiring a high, compensating wage. The key assumption to generate monopsony power is then an inability on the firms' part to implement discriminatory wages across its employees, which could be due to information asymmetries, i.e., the firm does not know how much each employee enjoys to work for it, or fairness considerations, i.e., wage discrimination is perceived as unfair with resulting consequences for morale and productivity. Resultingly, an expanding firm needs to raise the wages of all workers to attract new workers at the margin raising marginal costs perceived by the firm above the costs of hiring the new worker only. This mechanism thus reduces firms incentives to expand due to rising inframarginal wages and, hence, leads to an insufficiently low demand for workers. The following model formalizes these ideas for the case of R&D workers and traces their impact on growth and innovation in a general equilibrium framework, which forms the basis of the subsequent empirical analysis.

2.1 Model Description and Competitive Equilibrium

Time is discrete and indexed by t. The economy is populated by a representative household and has a final goods and intermediate production sector. The latter consists of a unit mass of firms that own the production rights to their intermediates and invest in innovation to create more thereof. I introduce the household next, followed by a description of the production and innovation sectors.

Workers and Labor Markets A representative household owns all firms and provides labor in form of production workers $L_{P,t}$ and research workers $\{\ell_{kt}\}$ to firms $k \in [0, 1]$. The income from production workers, $W_{P,t}$, research workers $W_{R,kt}$, bond holdings $R_t \cdot B_t$, and firm ownership Π_t can either be consumed C_t or invested in a riskless bond B_{t+1}. Flow utility takes the Balanced Growth Preferences structure and is discounted at rate β (King et al., 1988). The household solves

$$
\begin{aligned}
\max_{\{C_t, L_{P,t}, \{\ell_{kt}\}_{k\in[0,1]}\}} \quad & \sum_{t=0}^{\infty} \beta^t \cdot \frac{\left(C_t \cdot v(L_{P,t}, L_{R,t})\right)^{1-\sigma} - 1}{1-\sigma} \\
\text{with} \quad & v(L_{P,t}, L_{R,t}) = \exp\left(-\frac{\epsilon}{1+\epsilon}\left(\alpha_P \left(\frac{L_{P,t}}{\alpha_P}\right)^{\frac{1+\epsilon}{\epsilon}} + \alpha_R \left(\frac{L_{R,t}}{\alpha_R}\right)^{\frac{1+\epsilon}{\epsilon}}\right)\right), \\
& L_{R,t} = \left(\underline{\ell} + \frac{1}{1+\xi}\right)^{-1} \cdot \left(\int_0^1 \ell_{kt} \cdot \left(\underline{\ell} + \frac{1}{1+\xi}\left(\frac{\ell_{kt}}{L_{R,t}}\right)^{\xi}\right) dk\right), \\
\text{and} \quad & B_{t+1} + C_t = R_t \cdot B_t + W_{P,t} \cdot L_{P,t} + \int_0^1 W_{R,kt} \cdot \ell_{kt} \cdot dk + \Pi_t.
\end{aligned} \tag{1}
$$

A couple of remarks are in order. First, the household has convex labor disutility for production and research work, $L_{P,t}$ and $L_{R,t}$ respectively. Importantly, both types of work enter separately such that the household does substitutes between them. This assumption captures the idea that production and research labor are very different tasks requiring very different skills or training and, in practice, might be executed by different workers. Here, $\epsilon \geq 0$ is the labor supply elasticity and the disutility shifters, α_P and α_R, control the labor supply level such that larger values imply more supply at a given wage.

Second, research work is an aggregate over the supply to individual firms, which captures the idea that firms might be imperfect substitutes from the perspective of workers. Intuitively, being a researcher for Apple or Ford Motors might require very different skills such that workers cannot easily move between both firms. The aggregator is governed by two parameters $\{\xi, \bar{\ell}\}$ that serve different purposes. The first parameter ξ makes firm-specific labor supply less elastic for all firms. The second parameter $\bar{\ell}$ makes labor supply log-convex such that it becomes less elastic the larger the firm is relative to the overall supply. Note that if $\bar{\ell} = 0$, the aggregator becomes the CES type and with $\xi = 0$ we have a standard linear aggregator.

Finally, the budget constraint reflects that different R&D firms might have to pay different wages $W_{R,kt}$ to attract the desired number of R&D workers. It also imposes that firms cannot differentiate among inventors and have to pay a single firm-level wage. This assumption is crucial to generating monopsony power in this model. I discuss the implication of price discrimination in the discussion section.

Final Production. A representative firm hires production labor $L_{P,t}$ at wage $W_{P,t}$ and buys intermediate inputs $\{x_{jt}\}_{j\in\mathcal{Q}_t}$ at price p_{jt} to produce output Y_t. The firm solves

$$\max_{L_{P,t},\{x_{jt}\}_{j\in\mathcal{Q}_t}} Y_t - W_{P,t}\cdot L_{P,t} - \int_{\mathcal{Q}_t} p_{jt}\cdot x_{jt}dj \quad \text{s.t.} \quad Y_t = L_{P,t}^{1-\alpha}\int_{\mathcal{Q}_t} z_{jt}^{1-\alpha}\cdot x_{jt}^{\alpha}dj, \tag{2}$$

where z_{jt} is a demand-shifter.

Intermediate good producers. Intermediate goods in the economy are protected by patents such that they can only be produced by their proprietor. There is a unit mass of intermediate good firms, which act as proprietors, with constant unit cost ψ. For each intermediate good, the proprietor solves

$$\pi_{jt} = \max_{x_{jt}} \quad p_{jt}\cdot x_{jt} - \psi\cdot x_{jt} \tag{3}$$

subject to the product demand curve from the final production sector.

Innovation Each intermediate goods firm can hire ℓ_{kt} research workers to produce new blueprints M_{kt+1} in the subsequent period subject to wage cost $W_{R,kt}$ according to production function

$$M_{kt+1} = Q_t\cdot A_k\cdot \ell_{kt}^{\gamma}, \tag{4}$$

where $Q_t = \int_0^{\mathcal{Q}_t} z_{kt}\cdot dk$ is the quality adjusted mass of products, which is also the aggregate state of technology, and A_k is a firm-specific productivity shifter.

New blueprints are added to their stock of protected products such that the quality adjusted mass of inventions Q_{kt} evolves according to

$$Q_{kt+1} = M_{kt+1}\cdot z_{kt+1} + Q_{kt}. \tag{5}$$

The product-specific demand-shifter is determined at the point of invention and is identical to all products invented by the same firm in the same period.[5] Firms' demand-shifter is persistent and evolves according to

$$\ln z_{kt+1} = (1-\rho)\cdot\mu + \rho\cdot\ln z_{kt} + \sigma\cdot\nu_{kt+1} \quad \text{with} \quad \nu_{kt+1}\sim N(0,1). \tag{6}$$

[5] Alternatively, one could assume that demand for all products fluctuates concurrently at the firm level. Such an assumption will affect the precise algebra of the model, but not the qualitative or quantitative properties of the model with respect to the innovation sector.

Intermediate firms hire researchers to maximize their value

$$V_t(Q_{kt}, z_{kt}) = \max_{\ell_{kt}} \left\{ \int_{j \in Q_{kt}} \pi_{jt} \cdot dj - W_{kt} \cdot \ell_{kt} + R_{t+1}^{-1} \cdot \mathbb{E}_t \left[V_{t+1}(z_{kt+1}, Q_{kt+1}) | z_{kt} \right] \right\} \tag{7}$$

subject to the labor supply curve and the evolution of their portfolio of inventions.

Growth. The aggregate state of technology $Q_t = \int_0^1 Q_{kt} \cdot dk$ evolves according to

$$Q_{t+1} = Q_t + \int_0^1 M_{kt+1} \cdot z_{kt+1} \cdot dk. \tag{8}$$

The private equilibrium definition is standard and formalized in Definition 1.

Definition 1 (Competitive Balanced Growth Path Equilibrium)**.** *A sequence of quantities and prices such that (a) firms maximize profits and firm value, (b) markets clear, (c) quantities grow at a constant rate.*

2.2 Planner's Problem

To study optimal policy, it is useful to introduce the planner problem. The planner chooses quantities to maximize expected utility:

$$\begin{aligned}
\max \quad & \mathbb{E}_t \sum_{t=0}^{\infty} \beta^t \cdot \frac{(C_t \cdot v(L_{P,t}, L_{R,t}))^{1-\sigma} - 1}{1-\sigma} \\
\text{with} \quad & v(L_{P,t}, L_{R,t}) = \exp\left(-\frac{\epsilon}{1+\epsilon} \left(\alpha_P \left(\frac{L_{P,t}}{\alpha_P} \right)^{\frac{1+\epsilon}{\epsilon}} + \alpha_R \left(\frac{L_{R,t}}{\alpha_R} \right)^{\frac{1+\epsilon}{\epsilon}} \right) \right), \\
& L_{R,t} = \left(\underline{\ell} + \frac{1}{1+\xi} \right)^{-1} \cdot \left(\int_0^1 \ell_{kt} \cdot \left(\underline{\ell} + \frac{1}{1+\xi} \left(\frac{\ell_{kt}}{L_{R,t}} \right)^{\xi} \right) dk \right), \\
& C_t = L_{P,t}^{1-\alpha} \int_{\mathcal{Q}_t} z_{jt}^{1-\alpha} \cdot x_{jt}^{\alpha} \cdot dj - \int_{\mathcal{Q}_t} \psi \cdot x_{kt} \cdot dk, \\
& Q_{t+1} = \int_0^1 M_{kt+1} \cdot z_{kt+1} \cdot dk + Q_t \quad \text{and} \quad M_{kt+1} = Q_t \cdot A_k \cdot \ell_{kt}^{\gamma}
\end{aligned} \tag{9}$$

subject to the law of motion for firm-level R&D productivities. The associated equilibrium definition is provided in Definition 2.

Definition 2 (Planner Balanced Growth Path Equilibrium)**.** *A sequence of quantities that solve the planner problem (9) and productivity grows at a constant rate.*

2.3 Monopsony in R&D and Growth

The characteristic feature of monopsony power is that firms' wages respond to their demand for labor and that firms take this effect into account. Proposition 1 highlights the first property in the model by showing that firms' R&D wages respond to their demand for R&D workers.[6] Furthermore, this sensitivity is stronger for firms that are already larger in the case of log-concave labor supply with $\bar{\ell} > 0$. Resultingly, firms' demand for R&D workers becomes less sensitive to R&D productivity shocks or targeted subsidies as they get larger if $\bar{\ell} > 0$.

How do these properties compare to the allocation in a planner equilibrium? It turns out that the sensitivities to R&D productivity or subsidies coincides in the planner and competitive equilibrium as long as monopsony power is log-linear, i.e., $\bar{\ell} = 0$. With log-concave R&D labor supply, the demand for R&D workers is less sensitive in the competitive equilibrium as the sensitivity of wages changes alongside the wages or marginal products themselves, which is only taken into account by profit maximizing firms.

Proposition 1 (Wages in the R&D sector)**.** *Consider an R&D subsidy* $(1 - \tau_{kt})$*. The elasticity of the firm's R&D wage with respect to a change in R&D workers induced by a small change in the subsidy rate is given by*

$$\left.\frac{\partial \ln W_{R,kt}}{\partial \ln \ell_{kt}}\right|_{\Delta \tau_{kt}} = \xi \cdot \frac{(\ell_{kt}/L_{R,t})^{\xi}}{\bar{\ell} + (\ell_{kt}/L_{R,t})^{\xi}}, \tag{10}$$

which is positive if $\xi > 0$ *and, in addition, increasing in the firm's relative R&D employment if* $\bar{\ell} > 0$*. Furthermore, firms' equilibrium R&D employment becomes less sensitive to productivity shocks with monopsony power,* $\xi > 0$*, and particularly so for larger firms if* $\bar{\ell} > 0$ *as well. Relative to a planner equilibrium, firms' R&D employment is equally sensitive to productivity shocks in the competitive equilibrium as long as* $\bar{\ell} = 0$ *and becomes less sensitive in the case of* $\bar{\ell} > 0$ *as inventor employment increases.*

So, what happens to allocation in equilibrium in an economy with monopsony power. Proposition 2 highlights two effects. Firstly, monopsony power lowers the equilibrium R&D effort vis-a-vis a world without it as long as the aggregate supply of inventors is not perfectly inelastic. Even in absence of monopsony power, the competitive equilibrium features insufficient R&D due to an insufficient market size coming from the monopoly distorting in the product market and intertemporal knowledge externalities. Monopsony

[6] Derivations and proofs are provided in Appendix A.

power thus further increases this gap. Secondly, with log-concave labor supply, the relative allocation of R&D workers in the competitive equilibrium is skewed towards small firms as the former take advantage of their higher monopsony power by reducing their demand for R&D workers. Thus, in this case, not only the aggregate level of R&D employment is too low, but R&D workers are also not optimally allocated across firms from the perspective of a planner, which further reduces economic growth. I refer to the latter as misallocation.

Proposition 2 (Allocative efficiency in the R&D sector)**.** *Suppose labor market power is homogeneous, i.e.* $\bar{\ell} = 0$*, then there is insufficient demand for R&D in the competitive equilibrium, however, the relative allocation of R&D workers across firms is efficient. The efficient equilibrium can be achieved by a combination of untargeted output and R&D subsidies. Conversely, suppose that the aggregate level of R&D workers is fixed, i.e.* $\epsilon \to 0$*, then the demand for R&D workers is efficient as long as labor market power is homogeneous. With differences in R&D labor market power, the allocation of R&D workers in the competitive equilibrium is tilted towards smaller firms. An efficient equilibrium can only be achieved by targeted R&D subsidies.*

What are the policy implications? In the case of common monopsony power, the planner equilibrium can be achieved by a general subsidy to firms' R&D activity or, alternatively, by subsidizing R&D workers. Such a subsidy becomes ever more important the more elastic the supply of R&D workers in the economy. In the case of heterogeneous monopsony power, general R&D subsidies are insufficient and targeted interventions become necessary. The optimal (marginal) R&D subsidy rate is larger for firms hiring more inventors.

Optimal policy under size-dependent monopsony power suggests that large employers of inventors should hire even more of them and, thus, appear to invest too little into R&D. This result is in stark contrast to some recent contributions in the literature that generally argue to large firms might do too much R&D relative to small firms (Aghion et al., 2022; de Ridder, 2023). Both views are easily reconciled when considering the source of heterogeneity innovation activity. In my model, heterogeneity is driven by real productivity differences across firms that a planner would also consider when allocating R&D workers. In contrast, some of the heterogeneity in R&D activity across firms in the aforementioned papers is driven by heterogeneous abilities to profit from innovation that lead large firms to do too much R&D relative to a planner, who would not take into account firms' ability to charge higher markups when deciding on the optimal allocation of R&D resources. In practice, both forces might be partly offsetting with ambiguous net-effects. I focus on quantifying the effect of monopsony power only in this paper.

2.4 The Tell-Tale Signs of (Size-dependent) Monopsony Power

Before providing evidence on monopsony power in R&D markets, I want to point out a caveat for any potential empirical investigation and highlight a model prediction that can act as tell-tale sign for monopsony power.

First, Proposition 1 highlights that monopsony power materializes in form of a finite labor supply elasticity in response to firm-specific demand shocks. Proposition 3 further emphasizes the necessity of using firm-level shocks for identification. In particular, the equilibrium response of wages to aggregate shocks, such as an economy-wide R&D subsidy, is independent of firms' market power and depends only on the aggregate labor supply elasticity for R&D workers. Thus, it is impossible to estimate the extent of monopsony power in this model when considering aggregate shocks. Direct estimates of the labor supply elasticity can only be recovered with firm-specific inventor demand shocks.

Proposition 3. *The elasticity of firms' inventor wages with respect to their employment as induced by a small change in the general R&D subsidy rate* $1-\tau_t$ *is given by*

$$\left.\frac{\partial \ln W_{R,kt}}{\partial \ln \ell_{kt}}\right|_{\Delta\tau_t} = \frac{1}{\epsilon}, \tag{11}$$

which is constant across firms regardless of their monopsony power. Furthermore, under such a policy change, the relative allocation of R&D workers $\ell_{kt}/L_{R,t}$ *remains constant.*

Second, there are tell-tale signs of monopsony in the model that do not require estimating the labor supply elasticity. In particular, under monopsony power, the average product of an R&D worker, expected or realized, is an increasing function of firms' R&D employment as shown in Proposition 4. Furthermore, the R&D return, or the ratio of R&D output to its costs, is an increasing function of R&D employment iff monopsony power is increasing in R&D employment. Thus, finding a positive correlation between R&D returns and R&D employment is a potentially strong signal of size-dependent monopsony power.

Proposition 4. *Let the expected R&D return of a firm be the ratio of the expected value created from innovation to the total cost. Its equilibrium value is given by*

$$\textit{Expected R\&D Return}_{kt} \equiv \frac{M_{kt+1}\cdot \mathbb{E}_t[z_{kt+1}|z_{kt}]\cdot \tilde{\pi}_{t+1}/R_{t+1}}{W_{R,kt}\cdot \ell_{kt}} = \frac{1}{\gamma}\cdot(1+1/\epsilon_{kt}). \tag{12}$$

Resultingly, it is constant across firms iff $\bar{\ell}=0$ *and increasing in* ℓ_{kt} *for* $\ell_{kt}>0$*. The realized R&D returns is increasing in* ℓ_{kt} *iff* $\bar{\ell}>0$*. Similarly, the expected average product of an R&D worker is increasing in* ℓ_{kt} *if* $\xi>0$ *and* $\bar{\ell}\geq 0$*, and constant otherwise.*

3 Evidence

This section provides evidence on monopsony power in the market for inventors in the U.S. I first describe how I measure key variables in my estimation, including R&D employment and wages, before discussing the estimation strategy and presenting the estimates.

3.1 Data

My data combine information on the financial performance and innovation activity of US listed firms. I obtain financial data from WRDS Compustat, who collect and harmonize them based on mandatory filings by the company. The data reach back to 1959 and their availability is tied to the company's listing status. Variables of interest include R&D expenditure (`xrd`), employment (`emp`), and stock market returns. I combine this data with information on firms' patenting activity using the crosswalk between firms and patents developed in Kogan et al. (2017). The patent data from Kogan et al. (2017) and the USPTO's Patentsview database includes information on firms' granted patents, including application date and technology classification, and the inventors that contributed to the patent.

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 newly granted patents a prime source for information on firms' innovation activity. Nonetheless, it is well known that not all inventions are patented such that patent-based information may be incomplete (Cohen et al., 2000; Mezzanotti and Simcoe, 2023).

The primary variables of interest when investigating monopsony power are employment and wages. I measure inventor employment using patent records. I link inventors across patents using the USPTO's disambiguation and assign them to firms based on whether they are listed on a firm's newly-granted patents within the relevant 5-year window, where the patent is recorded in its application year. I assign the firm a full time equivalent share of the inventor based on its share in the inventor's new patent portfolio and aggregate to the firm-level by summing over all inventors. This measure may be incomplete, e.g., because not all active researchers at the firm are listed on a patent within a given period, however, it provides a readily available measure of innovators contributing to the firms' patent output. Using a 5-year window is intended to reduce measurement error.

I measure inventor wages as the ratio of R&D expenditure over a 5-year window divided by inventor employment over the same window. This measure suffers from three potential concerns. First, not all R&D expenditure is on labor inputs as R&D often also requires material inputs and machinery. NSF statistics suggest that R&D is very labor intensive with a labor share of costs of 79% in 2021.[7] Thus, we might expect some measurement error from this misspecification, but it is likely small as I discuss in Section 4. Second, my measure of inventors might be incomplete as discussed above, which will add measurement error. Third, the implicit assumption when measuring inventors is that R&D projects result in a patent application within a given year. In practice, there might be research projects with larger time horizons, which could results in a misalignment between R&D expenditure and recorded patents that shows up as measurement error. My analysis, thus, needs to take into account potential measurement error in R&D wages.

As discussed in the previous section, the R&D return can be informative about monopsony power. I measure it as the ratio of valuations of new patent to previous year's R&D expenditure at the 5-year horizon:

$$\texttt{R\&D Return}_{it} \equiv \frac{\sum_{s=0}^{4} \texttt{Patent Valuations}_{it+s}}{\sum_{s=0}^{4} \texttt{R\&D Expenditure}_{it-1+s}}. \tag{13}$$

I also construct measures of firms' dominance in their technology markets and inventor specialization, which are described in the text and Appendix B.

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 has about 15,000 observations for 900 firms and 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 B for further data details.

3.2 Estimation Approach

The inverse labor supply elasticity for inventors determines the extent of monopsony power in the model presented in the previous section and is, thus, key to understanding its impact on the innovation economy. The elasticity can be estimated by regressing log changes

[7] I calculate this figure using Table 10 in the NSF's Business Enterprise Research and Development Survey statistics for 2019. In my calculations I exclude "other" R&D expenditure and "other purchased services" and add 1/3 to the expenditure on depreciation to capture cost of capital assuming a 5% interest rate and 15% depreciation rate. Total R&D expenditure on labor includes "salaries, wages, and fringe benefits," "stock-based compensation," and "temporary staffing." The labor share in all R&D expenditure is 67%, while the labor share for adjusted R&D expenditure is 79%.

in the inventor wage on changes in log inventor employment as shown in equation (14) (Manning, 2003). 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.

$$\Delta \ln \text{Inventor Wage}_{it} = \bar{\epsilon} \times \Delta \ln \text{Inventors}_{it} + \alpha_{j(i)\times t} + \varepsilon_{it} \tag{14}$$

Estimating this equation in OLS can lead to biased estimates in the presence of labor supply shocks, which simultaneously affect wages and employment, and, thereby, violate the exclusion restriction. For example, if workers exogenously become more attracted to a firm, we might expect that it is can lower wages, while hiring more workers. However, this variation does not identify the response of wages if the firm wanted to expand employment in absence of such a shock. In short, supply shocks confound the estimation of a supply elasticity, and we, thus, need demand shocks for identification.

To address this concern, I propose to use stock market returns as an instrument for inventor employment, which follows **?**'s identification strategy for the overall labor supply elasticity. The instrument is relevant if stock market returns reflect changes in firm productivity or consumer demand that incentivize it to expand production. Expansion then increases the market size for new products, which gives the firms an incentive to expand R&D as well. The exclusion restriction requires that stock market returns do not affect inventor wages growth other than through their impact inventors employment growth.

I connect the inverse labor supply elasticity to inventor employment with an interaction term for firms with above median R&D employment in the previous year. Under size-dependent monopsony power, we expect a positive coefficient on the interaction term, as firms with large inventor employment face a high inverse labor supply elasticity. I follow a similar approach for above and below median R&D return, which is also linked to the inventor supply elasticity as discussed in the previous section.

$$\begin{aligned} \Delta \ln \text{Inv. Wage}_{it} = \quad & \epsilon_l \times \Delta \ln \text{Inv.}_{it} \\ & + (\epsilon_h - \epsilon_l) \times \Delta \ln \text{Inv.}_{it} \times \{\text{Above Median Inventors}\}_{it} \\ & + \beta \{\text{Above Median Inventors}\}_{it} + \alpha_{j(i)\times t} + \varepsilon_{it} \end{aligned} \tag{15}$$

The exclusion restriction for the interaction terms requires that the growth rate of R&D wages is not linked differentially to stock returns for larger firms other than through their impact on R&D employment growth.

There are several potential identification challenges. First, stock market returns may partly reflect labor supply shocks if they increase firm value.[8] The estimated elasticity may then be downwards biased as supply shocks, such as preference shocks, lower wages and raise employment. These shocks may also bias the interaction coefficient, e.g., if labor supply shocks are more important for firms with larger R&D employment.[9] Second, incentive pay for researchers, e.g., via granted stock options or payment in shares, may lead to a violation of the exclusion restriction by inducing a correlation between returns and inventor wages unrelated to inventor employment.[10] However, this is only a concern if the incentive pay is structured such that stock market returns affect the level of compensation. [11] Incentive pay could also bias estimate of the interaction regression, e.g., if firms with larger R&D employment rely more on it. Finally, the measured R&D wages include non-labor expenditure and, thus, wage growth may measured with error. Such measurement error biases the regressions if it is systematically related to the instrument.[12] I consider this threat together and incentive pay explicitly when quantifying the aggregate implications of R&D monopsony power.

3.3 Results

I report the first stage results in Appendix Table C.1. In short, the first stage looks as expected with a positive correlation between inventor employment growth and stock market returns. The F-statistics indicate a comfortably high level of power for my instruments.

My estimation results, as reported in Table 1, reveal three novel findings. First, the estimated inverse labor supply elasticity is positive and significant. A 10% increase in employment requires 9.6% higher wages. For comparison, **?** estimates an elasticity of 0.84 for high-skilled workers using LEHD data on wages and employment, which is well within the confidence interval of my estimate. The estimated elasticity suggests that workers only receive half their marginal product in wages. Second, firms with a large inventor workforce face less elastic inventor supply. A firm with above median inventors faces an elasticity of $0.410 + 1.245 \approx 1.7$ implying that a 10% increase in employment requires 17% larger wages.

[8] Importantly, these supply shocks need to apply to the market for inventors rather than other workers. A shock that lowers required wages for the non-inventor workforce without affecting required wages of inventors does not violate the exclusion restriction.

[9] For example, larger employers might rely more on their reputation to hire and retain inventors, which may expose them more to preference stocks.

[10] About 12% of total labor compensation in R&D is stock-related (NSF BERDS, 2019).

[11] Alternatively, stock-based compensation is not a concern if it merely affect how compensation is paid out, e.g., 15% in stocks, rather than the level of compensation. I discuss alternative models of such bonus payments in Appendix A.2.

[12] I discuss this issue in detail in Appendix A.3. The bias depends, among other things, on the elasticity of substitution between materials and inventors.

These estimates suggest that inventors working for large innovative firms receive 37% of their marginal product in wages, while R&D workers at small innovative firms receive 71% thereof. Note, however, that these estimates do not imply that wage levels are larger for smaller R&D employers as marginal products may differ substantially. Third, column (3) reveals that firms with large R&D return also face less elastic inventor supply, which is predicted by the theory developed in the previous section. Differences compared to those for inventor employment, which may reflect that R&D returns reflect other frictions apart from differences in the R&D supply elasticity.

Table 1: Inventor Inverse Labor Elasticity Estimates

	(1)	(2)	(3)
		$\Delta \ln \texttt{Inventor Wage}_{it}$	
$\Delta \ln$ `Inventors`	0.963***	0.410**	0.817**
	(0.198)	(0.203)	(0.325)
— × {Top 50% Inventors}		1.245***	
		(0.446)	
— × {Top 50% R&D Return}			1.079**
			(0.512)
Interaction term		✓	✓
First stage F stat. (Main)	96	48	39
First stage F stat. (Inter.)		71	60
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 consider several robustness exercises. First, one concern might be that expanding firms do not only hire more, but also better inventors. Observed wage growth may then reflect a composition effect rather than an increase in quality-adjusted wages. I investigate this concern by constructing proxies for inventor productivity and controlling for them in my regression.[13] The associated regression results, as reported in Appendix Table C.2, suggest that inventor quality is positively associated with inventor wages, however, this relationship does not quantitatively alter the estimated inventor supply elasticities.

Second, I control for pre-trends by adding lagged employment and wage growth as in **?**, which yields significantly larger estimates as reported in Appendix Table C.4. Adding firm fixed effects yields similar results as reported in Appendix Table C.3.

[13] I follow an AKM approach for annual R&D output for individual inventors and construct annual firm-level measures of inventor quality by averaging over the inventor fixed effects for all employed inventors.

3.4 Additional Evidence

Before concluding the empirical section, I want to highlight two additional model predictions that are born-out by the data. First, the model predicts a positive correlation between inventor employment and R&D return as long as there is size-dependent monopsony power. I confirm this relationship in Table 2. In column (1) I find that a 10% increase in the number of inventors hired is associated with a 2.3% increase in the R&D return. This correlation becomes even stronger once we adjust for inventor quality, which might be appropriate measure since inventor quality is homogeneous in the model, as shown in columns (2) and (3). Finally, column (4) confirms that this relationship is indeed driven by inventor employment and not overall employment. Overall employment is not a significant predictor of R&D returns conditional on inventor employment and its inclusion does not quantitatively change the relationship between R&D employment and R&D return.

Table 2: R&D Returns and Inventor Employment

	(1)	(2)	(3)	(4)	(5)
			ln **`R&D Return`**		
ln `Inventors`	0.228***	0.253***	0.263***		
	(0.032)	(0.031)	(0.033)		
ln `Employment`			-0.018		
			(0.026)		
ln `Firm Dominance`				0.139***	
				(0.041)	
ln `Inventor Specialization`					0.229***
					(0.080)
Quality adjustment		✓	✓		
R2-Within	0.07	0.15	0.15	0.01	0.00
Observations	11,845	11,844	11,812	10,477	11,828

Note: This table reports OLS coefficient estimates. Columns (2)-(3) adjust inventor employment for quality. See text and Appendix B for details. Standard errors are clustered at the NAICS6 level.

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

Second, size-dependent monopsony power predicts a correlation between the R&D returns and firm expansion. Drivers of firm expansion, as captured, e.g., by firms' stock returns or productivity shocks, should, thus, be positively correlated with the R&D return. I confirm this relationship in Table 3. Both prior stock market returns and productivity changes are positively correlated with the R&D return. Thus, R&D returns appear to increase during firm expansion, in line with the size-dependent monopsony power.

Finally, monopsony power is often associated with a lack of outside options for workers

Table 3: R&D Returns and Firm Expansion

	(1)	(2)
	ln R&D Return	
Lagged Excess Return	0.258***	
	(0.031)	
Lagged TFP Growth		0.219***
		(0.044)
R2-Within	0.01	0.00
Observations	10,065	7,922

Note: This table reports OLS coefficient estimates. See text and Appendix B for details. Standard errors are clustered at the NAICS6 level.

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

(Schubert et al., 2023). I provide some further evidence on this idea in columns (4) and (5) of Table 2. First, I develop a measure of firm dominance in its specific inventor labor market. Defining this market is not straight-forward, however, technology classifications of patents might provide a reasonable approximation. Thus, I calculate the share of inventors employed by the firm among those patenting in the relevant technology classes.[14] Column (4) confirms that this measure is significantly associated with R&D return, in line with a size-dependent monopsony interpretation. Vis-à-vis the general R&D employment regression, this result confirms that the regression is not just driven by differences in the size of the technology market across firms. A lower regression coefficient might be explained by measurement error in the firm dominance measure.

Second, a lack of outside options can be the product of specialization on the part of inventors. Thus, we might expect that firm that tend to hire more specialized inventors also have larger R&D returns. Column (5) confirms this conjecture. I measure inventor specialization through technology classes. For each inventor, I measure how similar the patents are that they worked on as measured by the distance of their technology classes. Inventors with small distances are more specialized.[15] I aggregate to the firm-level by taking an average over all employed inventors. Column (5) confirms that firms hiring more specialized inventors indeed have larger R&D returns—in line with the idea that they have more market power.

[14] I use the CPC classification, which has around 600 individual technology classes. A patent can belong to multiple technology classes and I treat the full list of classifications as the appropriate market.

[15] To reduce measurement error, I only calculate this measure for inventors with significant patent portfolio.

4 Quantification

The evidence presented in the previous section suggests a potentially meaningful role for monopsony power in the market for inventors. This section quantifies its impact on innovation and economic growth in an extension of the model presented in Section 2 that is calibrated it to match the evidence.

4.1 Quantitative Model

There are three challenges in using the model presented in Section 2 together with the evidence in Section 3 to investigate the importance of monopsony power in R&D for economic growth and innovation. First, my data is restricted to listed firms, which tend to be larger. Resultingly, I might overstate the importance of monopsony power by using evidence on large firms, which might have more monopsony power, while ignoring the 40% of R&D expenditure that is not accounted for by these firms.[16] Secondly, the model ignores intermediate inputs in R&D, which account for 20% of R&D costs in practice. As I discuss below, introducing intermediate inputs tends to dampen the importance of monopsony power as firms are able expand using intermediates instead of R&D workers. Finally, the model does not take into account pay linked to firm performance, which is common in practice, e.g., through stock-based compensation, and which may bias estimated firm-level labor supply elasticities downwards.[17]

I, thus, extend the baseline model to address these challenges. First, I introduce non-listed firms by allowing for two types of firms with different baseline R&D productivities $\{A_l, A_{nl}\}$. I fix the mass of firms for each type exogenously to match data from the NSF and denote the share of listed firms by ζ. As shown below, non-listed firms tend to have much smaller R&D budgets in practice, which the model interprets as having low R&D productivity. Resultingly, adding these firms to the model introduces a mass of firms with relatively low monopsony power as long as $\bar{\ell} > 0$, which reduces the overall impact of monopsony power over inventors on economic growth.

Second, I introduce stock-based compensation to account for a potential direct link between wages and firm performance. I assume that a fraction of the R&D wage is paid out in form of a fixed number of stocks in the next period that is set to constitute a constant share

[16] Total R&D expenditure in the Compustat sample in 2019 is 340 billion USD, while the NSF reports a total expenditure on R&D for all firms of 564 billion USD, implying that listed firms account for 60% of R&D expenditure. For 2000, this share is slightly higher at 72%.

[17] For example, Kline et al. (2019) estimate that a significant share of the value created from patent grants is captured by high-skilled workers in small firms. Card et al. (2018) and Friedrich et al. (2021) provide evidence of pass-through of firm shocks to worker wages.

of expected wages. The number of shares is set one period in advance such that workers at fortunate firm receive an unexpected pay rise and vice versa. Resultingly, expected wages remains the same, however, a fraction of the realized wage is directly linked to stockmarket returns for the firm. As discussed above, such a correlation constitutes a violation of the exclusion restriction for using stockmarket returns as an instrument for R&D productivity shocks when estimating the inverse labor supply elasticity. [18] Introducing this channel directly in the model allows me to take this empirical challenge into account when assessing the extent of monopsony power.

Finally, I augment the R&D production function to include intermediate inputs R_{kt} via a standard CES aggregator:

$$M_{kt+1} = Q_t \cdot A_k \cdot \left(\alpha_L^{\frac{1}{\sigma}} \cdot \ell_{kt}^{\frac{\sigma-1}{\sigma}} + (1-\alpha_L)^{\frac{1}{\sigma}} \cdot \left(\frac{R_{kt}}{Q_t} \right)^{\frac{\sigma-1}{\sigma}} \right)^{\gamma \cdot \frac{\sigma}{\sigma-1}}. \tag{16}$$

The new production functions nests the original one with $\alpha_L = 1$. The normalization by Q_t is necessary to allow for a balanced growth path. Intermediate inputs are produced 1-for-1 from the final outputs such that the aggregate resource constraint becomes:

$$Y_t = C_t + \int_0^1 x_{kt} \cdot dk + \int_0^1 R_{kt} \cdot dk. \tag{17}$$

Introducing intermediates is important as I proxy for R&D wages using the ratio of total R&D expenditure to R&D employment, which can be an imperfect measure if R&D expenditure partly reflects materials rather than labor cost. I show in Appendix A.3 that the changes in R&D per inventor become a potentially biased proxy for changes in R&D wages in this setup, where the bias depends on the elasticity of substitution between inputs as well as the markdown. Intuitively, firms increase their materials share when they expand if markdowns increase in R&D employment, which makes R&D expenditure more responsive relative to employment and, thus, R&D expenditure per worker becomes more responsive than R&D wages. Hence, one might over-estimate the degree of monopsony power in R&D when using R&D expenditure per worker rather than R&D wages, however,

[18] To give a numerical example, consider workers at firm k have an expected wage of 0.5 tomorrow and expect the firm to have value 1.5 as well. Furthermore, the stock-based compensation is set such that workers expect to earn 15% of their salary through stock-based compensation. Then, workers will receive $\frac{15\% \cdot 0.5}{1} = 0.05$ shares of the firm tomorrow. Suppose that wages are fixed, however, the value of the firm could be 2 or 1 tomorrow. Then, if the value goes up, workers receive $2 \cdot 0.05 + 0.85 \cdot 0.5 = 0.525$ in compensation. Alternatively, if the value goes down, workers receive a total of $1 \cdot 0.05 + 0.85 \cdot 0.5 = 0.475$ in compensation. This mechanism, thus, yields a positive correlation between stock returns and compensation even though expected wages are constant.

this bias can be accounted for within the model.

4.2 Calibration

I calibrate the quantitative model using a combination of external and internal calibration.[19] For the external calibration, I pick a standard value for discount factor $\beta = 0.97$, which together with a targeted growth-rate of 1.5% implies an annual risk-free interest rate of 5%. I follow the literature and calibrate the R&D scale elasticity as $\gamma = 0.5$ (Acemoglu et al., 2018). I calibrate the demand parameter α to achieve a markup in the product market $(1/\alpha)$ of 25%. Following Chetty et al. (2012), I set the aggregate labor supply elasticity to $\epsilon = 0.5$, such that an exogenous 1% rise wages would raise aggregate employment by 0.5%. Next, I set the elasticity of substitution between materials and labor in R&D at 0.8 following the evidence in Oberfield and Raval (2014) for the production sector.[20] Finally, I set the share of listed firms among R&D conducting firms to 5% based on the number of firms in my sample compared to the NSF R&D surveys.[21]

For the internal calibration, I target a set of macro and micro moments. At the aggregate level, I target an annual growth rate of 1.5% and a relative size of listed to non-listed firms of 35, which is in line with the relative size of firms in my sample and in the NSF aggregate statistics. These moments are particularly informative about the average R&D productivity of listed and non-listed firms $\{A_{nl}, A_l\}$. Furthermore, I target a total labor supply of 1/3, equivalent to 8 hours per day, whereof 14.6% work in R&D as in Acemoglu et al. (2018), to pin down the labor disutility parameters $\{\alpha_P, \alpha_R\}$. Finally, I target a labor share of 79% in R&D to pin down the relative importance of labor in the R&D production function α_L.[22] Next, I target a set of micro-moments from the data together with the evidence presented in the previous section. In particular, I target the standard deviation of the R&D growth rate for listed firms together with the auto-correlation of R&D to pin down the parameters of the demand process $\{\sigma, \rho\}$. I calculate these moments in the model using simulation and focusing on listed firms only. Finally, I target the regression evidence in columns (1) and (2) of Table 1 to inform the monopsony parameters $\{\xi, \bar{\ell}\}$.

[19]See Appendix A.4 for a full description of the quantitative model together with the (recursive) balanced growth path equilibrium.

[20]Unfortunately, there is no good evidence on the degree of substitution between capital and labor in the R&D process. Furthermore, it is not clear ex-ante whether that degree should be lower or higher than in the production process. On the one hand, human capital is critical to the generation of new ideas and, thus, R&D. On the other hand, some lab tasks might be highly prone to automation.

[21]My sample in 2000 has 1,068 firms, while the NSF reports 17,757 firms in total conducting R&D. For 2019, my sample has 480 firms, while the NSF reports a total of 9,890 firms conducting R&D. These figures imply a share of listed firms among R&D conducting firms of 4.9% and 6% for 2019 and 2000, respectively.

[22]I calculate this figure based on NSF data. See the calculations in Section 2 and Online Appendix E.1.

Table 4: Parameters and Calibration Targets

A. Parameters			
Parameter	Symbol	Value	Source
A.1. External calibration			
Discount factor	β	0.97	Standard value
Labor supply elasticity	ϵ	0.50	Chetty et al. (2012)
R&D scale elasticity	γ	0.50	Acemoglu et al. (2018)
Share of listed firms	ζ	0.05	NSF BRDIS 2019
Markup parameter	α	0.80	Terry (2023)
Elas. of substitution in R&D	θ	0.80	Oberfield and Raval (2014)
A.2. Internal calibration			
Labor disutility production	α_P	0.153	Direct
Labor disutility R&D	α_R	0.338	Direct
Labor weight in R&D	α_L	0.965	Direct
R&D productivity listed	A_l	0.380	Moment matching
R&D productivity unlisted	A_{nl}	0.020	Moment matching
Std. dev. R&D prod. shocks	σ	0.325	Moment matching
Autocorr. R&D prod. shocks	ρ	0.948	Moment matching
Avg. R&D supply elasticity	ξ	3.974	Moment matching
Rev. R&D supply elasticity	$\bar{\ell}$	$2.94{\cdot}10^4$	Moment matching

B. Moments			
Moment	Data	Model	Source
Growth rate	0.015	0.015	Data
Relative R&D listed vs non-listed	35	35	Data
Std. dev. of R&D growth-rate	0.316	0.316	Data
Autocorr. of R&D	0.922	0.89	Data
Wage elasticity	0.923	0.842	Data
Wage elas. for small R&D	0.41	0.426	Data
Δ wage elas. large R&D	1.245	1.245	Data
Labor share in R&D	0.79	0.79	Data
R&D employment	0.047	0.047	Acemoglu et al. (2018)
Production employment	0.286	0.286	Acemoglu et al. (2018)

Note: This table reports the calibrated parameters and targeted moments for the quantitative model. See text for details.

Table 4 reports the calibrated parameters, and the targeted moments for the internal calibration and their counterparts in the model. The model fits well with the largest deviation coming from the average wage elasticity. The parameters suggests that listed firms are significantly more productive in R&D and that there is a significant amount of monopsony power for larger firms.

As discussed in the empirical section, the model makes a range of predictions for the

R&D return under monopsony power. I confirm these in Table 5. Column (1) repeats the estimates from the data that were already reported in Section 3. Column (2) reports coefficients based on simulated data from the calibrated model and column (3) reports coefficients from the calibrated model when shutting down monopsony power by forcing firms to be price takers. The table confirms that the model qualitatively account for the relationship of R&D returns with the size of the inventor workforce, lagged excess returns, and lagged productivity growth under monopsony power. Quantitatively, the coefficients are of the same order of magnitude as the estimates in the data, but the correlations tend to be stronger for the inventor workforce and lagged excess returns in the model. Potential contributing factors may be a lack of measurement error in the model and that stock market returns are exclusively driven by R&D productivity in the model.

Table 5: R&D Returns and Monopsony

	(1)	(2)	(3)
A. Inventors		ln `R&D Return`	
ln `Inventors`	0.253***	0.529***	-0.021***
	(0.031)	(0.001)	(0.000)
B. Stock Market Return		ln `R&D Return`	
Lagged `Excess Return`	0.258***	0.457***	-0.030***
	(0.031)	(0.005)	(0.000)
C. Productivity growth		ln `R&D Return`	
Lagged `TFP Growth`	0.219***	0.159***	-0.010***
	(0.044)	(0.003)	(0.000)
Source	Data	Model	Model
Monopsony	—	Yes	No
Observations	7,922	99,994	99,994

Note: This table reports OLS coefficient estimates. Column (1) reports estimates from the sample. Columns (2) and (3) report estimates from simulated data from the model. See text and Appendix B for details. Standard errors are clustered at the NAICS6 level.

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

Finally, before discussing counterfactuals, I want to briefly highlight the importance of accounting for stock-based compensation and intermediate inputs. Table 6 reports the regression coefficients when estimating columns (1) and (2) in the Table 1 in the data and the model under alternative specifications. The first row reports the data, while the second row reports a calibration that does not include stock-based compensation nor intermediate inputs. The calibration provides a reasonable fit. The next rows add in stock-based compensation and intermediate inputs using the main calibration. The resulting regression coefficients imply much larger labor supply elasticities and, thus, suggest that the calibrated model overestimates the degree of monopsony power. The final row re-calibrates the model to the main specification, providing a similarly good fit, however, taking into account stock-based compensation as well as intermediate inputs. The exercise thus suggests that the main regression evidence cannot directly speak to the importance of these biases, however, we can take them into account in the model.

Table 6: Wage Regression in Data and Model

Model	Reg. (1)	Regression (2)	
	Main	Base	Inter.
Data	0.923	0.410	1.245
Baseline	0.884	0.410	1.355
+ *Stock-based compensation*	*0.891*	*0.413*	*1.375*
+ *Intermediate inputs*	*1.042*	*0.527*	*1.485*
+ *Both*	*1.048*	*0.530*	*1.497*
Adjusted	0.842	0.426	1.245

Note: This table reports regression coefficients from the data and from simulated data. The first row reports regression coefficients from Table 1. The second row reports coefficients from a calibrated model without stock-based compensation or intermediate inputs. The third to fifth row adjusted the calibrated model by adding stock-based compensation and intermediate inputs in R&D. Finally, the last row re-calibrates the model including stock-based compensation and intermediate inputs, and reports the final regression results.

4.3 Counterfactuals

Table 7 investigates the importance of monopsony power in the calibrated model. The first column reports values for the baseline model, while columns 2-4 present counterfactual economies. The "Full" counterfactual shuts down monopsony power entirely by forcing firms to take wages as given, as in a competitive equilibrium. The "Fixed $\tilde{L}_R$" scenario forces firms to act as price takers, but holds constant total R&D employment $\tilde{L}_R = \int_0^1 \ell_{kt} \cdot dk$ through a general tax on R&D employment. It, thus, focuses exclusively on the impact of reallocating R&D employment across firms in absence of monopsony. Finally, scenario $\Delta\tilde{L}_R$ leaves monopsony power in place, but implement the aggregate R&D employment of the "Full" counterfactual through a subsidy on R&D employment. This scenario, thus, allows us to understand how important lower demand for R&D workers is on the aggregate.

Table 7 suggests that monopsony power is very costly in the model. In its absence, growth accelerates from 1.5% per annum to 1.76%, yielding a welfare improvement by 6%

in consumption equivalent terms. Higher growth is partly fueled by a 13% increase in R&D employment, however, increasing employment alone cannot explain the $\frac{1.76\%-1.5\%}{1.5\%} \approx 17\%$ increase in growth suggesting an important role for reallocation across firms.[23] Importantly, as shown in Panel B, the model without monopsony power feature significantly more concentrated R&D employment. For example, the share of R&D expenditure accounted for by the 10% largest firms rises from 70% to 83%. Intuitively, rising monopsony power at the top held back their demand for R&D resources, such that the competitive equilibrium features more concentration. On the other hand, wage premia at the top remain relative constant, as shown in Panel C, partly to due a general rise in R&D wages in the middle of the R&D employment distribution.

Table 7: Counterfactuals for Full Calibration

Outcome	Baseline	No Monopsony		
		Full	Fixed $\tilde{L}_R$	$\Delta\ \tilde{L}_R$
A. Aggregates				
Growth rate	1.50%	1.76%	1.65%	1.59%
Δ Welfare	0.0%	6.2%	3.7%	2.2%
Δ R&D Employment	0.0%	12.8%	-0.0%	12.8%
Δ Firm Value	0.0%	-12.5%	-37.0%	9.4%
B. R&D Expenditure Share				
Top 10%	69.9%	83.0%	83.0%	70.0%
Top 5%	49.8%	69.9%	69.8%	49.8%
Top 2.5%	31.4%	48.3%	48.2%	31.5%
C. Wage Premium				
Top 10%	14.1%	13.0%	13.0%	14.1%
Top 5%	32.5%	27.4%	27.5%	32.6%
Top 2.5%	62.6%	62.9%	63.0%	62.8%

Note: This table reports key statistics from the calibrated model and counterfactual exercises.

Columns 3 and 4 suggest that reallocation across firms plays a more prominent role in the growth acceleration rather than the overall increase in R&D employment. In particular, reallocation alone yields an acceleration in economic growth by $1.65\% - 1.5\% = 0.15$ p.p., while changing total R&D employment "only" yields an additional 0.09 p.p. of economic growth.

[23] In absence of reallocation, the rise in R&D employment alone would have yielded an increase in growth equal to γ times the percent change in employment.

5 Discussion

Before concluding, I want to discuss three topics that may add some nuance to my findings.

Perfect price discrimination. A necessary assumption to generate monopsony power in the model is that firms cannot fully price discriminate among their workers. This assumption could be tested with inventor-level data by investigate whether expanding firms change only the wages of marginal workers or also of inframarginal ones. Seegmiller (2023) provides some evidence along those lines for “high-skilled” workers using the LEHD. Interestingly, he finds that labor supply elasticities are larger for new recruits rather than incumbent workers, which is the opposite of what a model with perfect price discrimination would predict if we are willing to assume that new recruits can be thought of as marginal workers. Nonetheless, I explore the idea of price discrimination in Appendix A.5.3 by introducing a flexible level of price discrimination. Higher levels of price discrimination naturally reduce the growth impact of monopsony power.

Firm entry and entrepreneurship. Another important consideration is firm entry and entrepreneurship. The exercise of monopsony power increases the value of the firms and, thus, might incentivize entry. Vice versa, forcing firms to be price takers significantly reduces their value, as shown in row four of Table 7. We might thus suspect that this leads to reduced entry, giving rise to a countervailing force to the increase in R&D employment. Thus, the overall impact of monopsony power may be dampened to the degree that monopsony power of large firms is an important motivation for firm entry. I discuss this issue further in Appendix A.5.2.

The nature of R&D productivity differences. As discussed above, the source of firm heterogeneity in R&D employment matters significantly when quantifying the impact of monopsony on economic growth. In my model, firms differ in their demand for inventors because their products are of different quality. This quality is directly reflected in their impact on aggregate productivity such that firms and planner agree on the relative allocation of R&D workers in a competitive benchmark economy. Monopsony power then distorts this allocation and, thereby, reduces economic growth. However, these results would be very different if, e.g., firms differed in their demand for inventors because they were differentially able to protect their intellectual property. In this scenario, monopsony power might actually be growth enhancing by offsetting a “distortion” vis-à-vis the planner allocation.

6 Conclusion

Politicians, commentators, and academics alike have raised concerned about the macroeconomic implications of limited competition in U.S. labor markets. This paper suggests that these concerns might be warranted when it comes to the market for inventors.

I reach this conclusion in three steps. In the first step, I present a heterogeneous firms endogenous growth model with monopsony power in the market for inventors. The model suggests two channels through which monopsony power harms economic growth and, thus, welfare. First, under monopsony power firms depress inventor wages by reducing their hiring. Resultingly, and if aggregate inventor supply is not perfectly inelastic, there are fewer inventors and, thus, there is less innovation. Second, monopsony power might be stronger for larger firms in which case they depress their demand for inventors disproportionally. Resultingly, inventor employment becomes artificially skewed towards smaller firms. This misallocation further depresses economic growth by failing to allocate workers towards firms with the largest marginal products.

In the second step, I present evidence suggesting that firms indeed have monopsony power over inventors and that this power is stronger for firms that employ many inventors. Key to these insights are estimates for firm-level inventor labor supply elasticities, which govern the extent of monopsony power in the model. I estimate these for a sample U.S. listed firms using an instrumental variable strategy. My estimates suggest that monopsony power is pervasive and indeed stronger for larger firms. I find that firms with above median inventor employment would lose only about 6.0% of their R&D workforce if they were to reduce their wages by 10%, while below median R&D employment firm would lose 24.4%.

In the final step, I present a quantitative extension of the baseline model and calibrate it to match my evidence on inventor labor supply elasticities. The calibrated model suggests that U.S. economic growth would increase from 1.50% to 1.76% per year in absence of monopsony power leading to a welfare improvement of 6%. Growth accelerates due to an expansion of inventor employment and an improvement in their allocation across firms.

These results suggest several avenues for future research. First, monopsony power over inventors in the corporate sector might affect their entrepreneurial activity. These considerations appear particularly relevant as big tech firms have engaged in a large number of acquisition of startups. Second, monopsony power might affect human capital investment by depressing its returns and by tilting investments towards skills that are less subject to monopsony power. Thus, monopsony power might not only affect the distribution of inventors across firms, but also the distribution of human capital across skills.

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Appendix

A Theory Appendix

A.1 Baseline Model

A.1.1 Characterization of Competitive BGP Equilibrium

In the following, I characterize the competitive equilibrium and subsequently highlight the implications for a Balanced Growth Path.

Household. Household optimization yields the familiar Euler equation:

$$\left(\frac{C_{t+1}}{C_t}\right)^{\sigma}\left(\frac{v(L_{P,t},L_{R,t})}{v(L_{P,t+1},L_{R,t+1})}\right)^{1-\sigma}=\beta\cdot R_{t+1}. \tag{A.1}$$

Along a BGP this gives rise to the standard relationship between (consumption) growth, interest rate, and discount factor: $(1+g)^{\sigma}=\beta\cdot(1+r)$.

The supply of production and research labor satisfies

$$\begin{aligned}\frac{W_{P,t}}{C_t}&=\left(\frac{L_{P,t}}{\alpha_P}\right)^{\frac{1}{\epsilon}}\\ \frac{W_{R,kt}}{C_t}&=\left(\frac{L_{R,t}}{\alpha_R}\right)^{\frac{1}{\epsilon}}\cdot\left(\underline{\ell}+\frac{1}{1+\xi}+\frac{\xi}{1+\xi}\cdot\int_0^1\left(\frac{\ell_{kt}}{L_{R,t}}\right)^{1+\xi}dk\right)^{-1}\cdot\left(\underline{\ell}+\left(\frac{\ell_{kt}}{L_{R,t}}\right)^{\xi}\right).\end{aligned} \tag{A.2}$$

As discussed above, ϵ governs the labor supply elasticity at the aggregate level, while ξ and $\bar{\ell}$ govern the firm-specific labor supply elasticities in the R&D sector. In particular, we have

$$\frac{\partial\ln L_{P,t}}{\partial\ln W_{P,t}}=\frac{\partial\ln L_{R,t}}{\partial\ln W_{R,t}}=\epsilon\qquad\text{and}\qquad\frac{\partial\ln\ell_{kt}}{\partial\ln W_{R,kt}}=\frac{1}{\xi}\cdot\frac{\bar{\ell}+(\ell_{kt}/L_{R,t})^{\xi}}{(\ell_{kt}/L_{R,t})^{\xi}}\equiv\epsilon_{kt},$$

where $W_{R,t}=\int_0^1\ell_{kt}\cdot W_{R,kt}\cdot dk$ is the average wage in the R&D sector. Note that $\epsilon_{kt}=\xi$ if $\bar{\ell}=0$, which is the CES case, and $\epsilon_{kt}\to\infty$ if $\xi\to 0$, which recovers the case where R&D workers are perfectly mobile across firms and wages are equalized within the R&D sector.

Production. The first order conditions of the final production firms gives rise to demand curves for production workers and intermediate goods

$$\frac{W_{P,t}}{C_t} = \frac{Y_t}{C_t} \cdot \frac{1-\alpha}{L_{P,t}} \quad \text{and} \quad p_{jt} = \alpha \cdot \left(\frac{L_{P,t} \cdot z_{jt}}{x_{jt}} \right)^{1-\alpha}. \tag{A.3}$$

Using this demand curve we can solve the associated firms' profit maximization problem. The equilibrium monopoly price p_M is constant across firms and given by $p_M = \frac{\psi}{\alpha}$. All prices are relative to the final good whose price is normalized to 1. Equilibrium quantities x_{kt} and profits are

$$x_{kt} = z_{kt} \cdot L_{P,t} \cdot \left(\frac{\psi}{\alpha^2} \right)^{-\frac{1}{1-\alpha}} \quad \text{and} \quad \pi_{kt} = \tilde{\pi}_t \cdot z_{kt}, \tag{A.4}$$

where $\tilde{\pi}_t = (1-\alpha) \cdot \alpha^{\frac{1}{1-\alpha}} \cdot \left(\frac{\psi}{\alpha}\right)^{-\frac{\alpha}{1-\alpha}} \cdot L_{P,t}$ is a common profit shifter.

Resultingly, output and consumption, i.e. output minus production costs, are given by

$$Y_t = Q_t \cdot L_{P,t} \cdot \alpha^{\frac{\alpha}{1-\alpha}} \cdot \left(\frac{\alpha}{\psi} \right)^{\frac{\alpha}{1-\alpha}} \quad \text{and} \quad C_t = Y_t - \int_0^{Q_t} \psi \cdot x_{kt} \cdot dk = (1-\alpha^2) \cdot Y_t. \tag{A.5}$$

Clearing the production labor market, we have

$$L_{P,t} = \alpha_P^{\frac{1}{1+\epsilon}} \cdot (1+\alpha)^{-\frac{\epsilon}{1+\epsilon}}. \tag{A.6}$$

Note: Insufficient supply in equilibrium depends on labor supply elasticity.
Conjecture: Fixing the insufficient supply of intermediates also fixes the labor market.

Innovation. Taking into account the characterization developed above, we can restate the firm's innovation problem as

$$\begin{aligned} V_t(z_{kt}, Q_{kt}) &= \max_{\ell_{kt}} \left\{ Q_{kt} \cdot \tilde{\pi}_t - W_{kt} \cdot \ell_{kt} + R_{t+1}^{-1} \cdot \mathbb{E}_t \left[V_{t+1}(z_{kt+1}, Q_{kt+1}) | z_{kt} \right] \right\} \\ \text{s.t.} \quad Q_{kt+1} &= M_{kt+1} \cdot z_{kt+1} + Q_{kt}, \quad M_{kt+1} = Q_t \cdot A_k \cdot \ell_{kt}^{\gamma} \quad \text{and} \quad W_{R,kt} = \mathcal{W}_{R,t}(\ell_{kt}). \end{aligned} \tag{A.7}$$

Along a Balanced Growth Path with $\tilde{\pi}_t = \tilde{\pi}$ and $R_{t+1} = R$ one can verify that

$$\frac{V_t(z_{kt}, Q_{kt})}{Q_t} = \tilde{v}(z_{kt}) + \mathcal{V} \cdot q_{kt}, \tag{A.8}$$

where I denote values normalized by Q_t in lower case, the value of quality-adjusted intermediates is $\mathcal{V} = R/(R-1) \cdot \tilde{\pi}$ and the value of innovation capability $\tilde{v}(z_{kt})$ is the solution to

$$\begin{aligned} \tilde{v}(z_{kt}) = & \max_{\ell_{kt}} \left\{ \frac{1}{R} \cdot \mathcal{V} \cdot m_{kt+1} \cdot \mathbb{E}[z_{kt+1}|z_{kt}] - \ell_{kt} \cdot w_{R,kt} + \frac{1+g}{R} \cdot \mathbb{E}_t[\tilde{v}(z_{kt+1})|z_{kt}] \right\} \\ s.t. \quad & m_{kt+1} = A_k \cdot \ell_{kt}^{\gamma} \quad \text{and} \quad w_{R,kt} = \mathcal{W}_R(\ell_{kt}). \end{aligned} \tag{A.9}$$

It is well known that there is a unique solution to this value function iteration problem. Furthermore, note that the choice of ℓ_{kt} is independent of the firm value such that the associated first order conditions are given by

$$\ell_{kt} = \left(\frac{\gamma \cdot A_k \cdot \mathbb{E}_t[\tilde{\pi}_{t+1} \cdot z_{kt+1}|z_{kt}]}{W_{kt} \cdot (1 + 1/\epsilon_{kt})} \right)^{\frac{1}{1-\gamma}}. \tag{A.10}$$

Derivations for the firm's value function maximization problem. The baseline problem is given by

$$\begin{aligned} & V_t(z_{kt}, Q_{kt}) = \max_{\ell_{kt}} \left\{ Q_{kt} \cdot \tilde{\pi}_t - W_{kt} \cdot \ell_{kt} + R_{t+1}^{-1} \cdot \mathbb{E}_t \left[V_{t+1}(z_{kt+1}, Q_{kt+1}) | z_{kt} \right] \right\} \\ & \text{s.t.} \quad Q_{kt+1} = M_{kt+1} \cdot z_{kt+1} + Q_{kt}, \quad M_{kt+1} = Q_t \cdot A_k \cdot \ell_{kt}^{\gamma} \quad \text{and} \quad W_{R,kt} = \mathcal{W}_{R,t}(\ell_{kt}). \end{aligned} \tag{A.11}$$

One can guess and verify that the firm's value function in equilibrium takes the form

$$\begin{aligned} & V_t(z_{kt}, Q_{kt}) = V_{Z,t}(z_{kt}) + V_{Q,t} \cdot Q_{kt}, \quad \text{where} \quad V_{Q,t} = \tilde{\pi}_t + \sum_{s=1} \left(\prod_{k=1,s} R_{t+k}^{-1} \right) \tilde{\pi}_{t+s} \\ & \text{and} \quad V_{Z,t}(z_{kt}) = \max_{\ell_{kt}} \left\{ -W_{R,kt} \cdot \ell_{kt} + R_{t+1}^{-1} \cdot \mathbb{E}_t \left[M_{kt+1} z_{kt+1} \cdot V_{Q,t+1} + V_{Z,t+1}(z_{kt+1}) | z_{kt} \right] \right\} \\ & \text{s.t.} \quad W_{R,kt} = \mathcal{W}_t(\ell_{kt}) \quad \text{and} \quad M_{kt+1} = Q_t \cdot A_k \cdot \ell_{kt}^{\gamma} \end{aligned} \tag{A.12}$$

Note that the choice of R&D input is independent of the evolution of $V_{Z,t}(z_{kt})$ and, thus, we can solve for optimal private R&D input as

$$\ell_{kt} = \left(\frac{\gamma \cdot Q_t \cdot A_k \cdot V_{Q,t+1}}{W_{R,kt} \cdot (1 + 1/\epsilon_{R,kt})} \right)^{\frac{1}{1-\gamma}}. \tag{A.13}$$

This demand function together with labor supply can be used to clear the labor market for R&D workers.

Derivations for the social planners innovation problem. Imposing the static equilibrium conditions derived above, we can restate the planner problem for R&D workers as

$$\begin{aligned}
\max \quad & \mathbb{E}_t \sum_{t=0}^{\infty} \beta^t \cdot \frac{(C_t \cdot v(L_P, L_{R,t}))^{1-\sigma} - 1}{1-\sigma} \\
\text{with} \quad & v(L_P, L_{R,t}) = \exp\left(-\frac{\epsilon}{1+\epsilon}\left(1 + \alpha_R \left(\frac{L_{R,t}}{\alpha_R}\right)^{\frac{1+\epsilon}{\epsilon}}\right)\right), \\
& L_{R,t} = \left(\underline{\ell} + \frac{1}{1+\xi}\right)^{-1} \cdot \left(\int_0^1 \ell_{kt} \cdot \left(\underline{\ell} + \frac{1}{1+\xi}\left(\frac{\ell_{kt}}{L_{R,t}}\right)^{\xi}\right) dk\right), \\
& C_t = Q_t \cdot L_P \cdot (1-\alpha) \cdot \left(\frac{\psi}{\alpha}\right)^{-\frac{\alpha}{1-\alpha}} \quad \text{and} \quad Q_{t+1} = Q_t \left(\int_0^1 A_k \cdot \ell_{kt}^{\gamma} \cdot z_{kt+1} \cdot dk + 1\right)
\end{aligned} \tag{A.14}$$

subject to the law of motion for firm-level R&D productivities. I denote the growth-rate of aggregate technology as $g_{t+1} = \int_0^1 A_k \cdot \ell_{kt}^{\gamma} \cdot z_{kt+1} \cdot dk$.

The first-order condition for R&D labor is given by

$$\gamma \cdot Q_t \cdot A_k \cdot \ell_{kt}^{\gamma-1} \cdot \mathbb{E}_t[z_{kt+1}|z_{kt}] \cdot \frac{\lambda_{t+1}^{Q}}{C_t \cdot \lambda_t^{C}} = \left(\frac{L_{R,t}}{\alpha_R}\right)^{\frac{1}{\epsilon}} \cdot \frac{\bar{\ell} + (\ell_{k,t}/L_{R,t})^{\xi}}{\bar{\ell} + (1+\xi)^{-1} + \frac{\xi}{1+\xi} \cdot \int_0^1 (\ell_{kt}/L_{R,t})^{1+\xi} \cdot dk}, \tag{A.15}$$

where the RHS is the shadow price of hiring an R&D worker, which coincides in formula with the competitive equilibrium.

We can solve for the marginal value of Q_t as

$$\lambda_t^{Q} = \lambda_t^{C} \cdot \frac{C_{t+1}}{Q_{t+1}} \left(1 + \sum_{s=1,\cdots,\infty} \left(\prod_{k=1,\ldots,s} (1 + g_{t+k}^{C})\right) \cdot \frac{\lambda_{t+s}^{C}}{\lambda_t^{C}}\right) \tag{A.16}$$

Note: Easy to show that consumption and productivity growth at the same rate in this model.

Define the shadow interest rate as $\tilde{R}_{t+1} = \lambda_{t+1}^{C}/\lambda_t^{C}$ and we can simplify further

$$Q_t \cdot \tilde{V}_{Q,t+1} \equiv \frac{\lambda_{t+1}^{Q} \cdot Q_t}{C_t \cdot \lambda_t^{C}} = \frac{1}{\tilde{R}_{t+1}} \left(1 + \sum_{s=1,\cdots,\infty} \left(\prod_{k=1,\ldots,s} \frac{1 + g_{t+1+k}}{\tilde{R}_{t+1+k}}\right)\right) \tag{A.17}$$

Defining the shadow wage appropriately we can solve for the first order conditions as

$$\ell_{kt} = \left(\frac{\gamma \cdot Q_t \cdot A_k \cdot \mathbb{E}_t[z_{kt+1}|z_{kt}] \cdot \tilde{V}_{Q,t+1} \cdot C_t}{\tilde{W}_{R,kt}} \right)^{\frac{1}{1-\gamma}} \tag{A.18}$$

A.1.2 Characterization of the Planner Equilibrium

Planner output and consumption:

$$\tilde{Y}_t = Q_t \cdot L_{P,t} \cdot \left(\frac{\psi}{\alpha} \right)^{-\frac{\alpha}{1-\alpha}} \quad \text{and} \quad C_t = (1-\alpha) Y_t \tag{A.19}$$

Planner production labor supply:

$$L_{P,t} = \alpha_P^{\frac{1}{1+\epsilon}} \tag{A.20}$$

A.1.3 Proofs

Proof of Proposition 1. WIP. □

Proof of Proposition 2. WIP. □

Proof of Proposition 3. WIP. □

Proof of Proposition 4. The first statement can be derived directly from the firm's first order conditions. The second statement follows from the fact that the average product is the R&D return times the R&D wage. □

A.2 Stock-based Compensation

R&D workers are often compensated through stocks. In 2019, the NSF reported that around 12% of total labor costs in R&D came through stock-based compensation. In the following, I highlight how this compensation structure can lead to a bias when estimating labor supply elasticities using stockmarket returns r_{kt} as an instrument using three examples. The examples highlight that alternative mechanisms for stock-based compensation lead to no, upwards, or downwards bias when estimating the (inverse) labor supply elasticity. Thus, the presence of stock-based compensation alone does not necessarily imply biased estimation.

I consider the following setup: Total compensation W_{kt} is given by

$$W_{kt} = W_{C,kt} + s_{kt} \cdot V_{kt}, \tag{A.21}$$

where $W_{C,kt}$ is the cash component of wages, s_{kt} denotes shares and V_{kt} the value of a share. I assume that the cash component is fully flexible and reflects any potential monopsony power, while considering alternative specifications for the stock-based compensation. Log changes in compensation can be approximated as

$$\Delta \ln W_{kt} \approx s_{C,kt} \cdot \Delta \ln W_{C,kt} + (1 - s_{C,kt}) \cdot (\Delta \ln s_{kt} + \Delta \ln V_{kt}) .$$

Throughout, I am interested in estimating the elasticity of R&D wages with respect to R&D employment using stockmarket returns, $r_{kt} = \Delta \ln V_{kt}$, as an instrument. The IV-estimator $\hat{\beta}_{IV}$ and unbiased estimate β are given by

$$\hat{\beta}_{IV} = \frac{\widehat{Cov}(r_{kt}, \Delta \ln W_{kt})}{\widehat{Cov}(r_{kt}, \Delta \ln \ell_{kt})} \qquad \text{and} \qquad \beta = \frac{Cov(r_{kt}, \Delta \ln W_{C,kt})}{Cov(r_{kt}, \Delta \ln \ell_{kt})},$$

where I assume instrument relevance, i.e. $Cov(r_{kt}, \Delta \ln \ell_{kt}) > 0$. Finally, firm's stock returns are assumed i.i.d. with an expected value of 0 and only total compensation is observed.

Example 1: Fixed share of compensation. Suppose workers receive a fixed share s of their compensation in stocks, while the remainder, $W_{C,kt}$ is paid out in cash. Total compensation is thus $W_{kt} = W_{C,kt} + s \cdot W_{kt}$. Simple algebra reveals then that $W_{kt} = (1-s)^{-1} \cdot W_{C,kt}$ such that overall compensation moves 1-for-1 with cash compensation. Resultingly, log changes in cash and overall compensation coincide, i.e. $\Delta \ln W_{kt} = \Delta \ln W_{C,kt}$, and the

IV estimator is unbiased.

Example 2: Fixed number of shares. Suppose the number of shares s_{kt} is determined one period in advance such that the expected share of compensation through stocks is s:

$$s = \frac{s_{kt} \cdot \mathbb{E}_{t-1}[V_{kt}]}{s_{kt} \cdot \mathbb{E}_{t-1}[V_{kt}] + \mathbb{E}_{t-1}[W_{C,kt}]}.$$

Since stock returns are i.i.d, they are orthogonal to the predetermined changes in share $\Delta \ln s_{kt}$. Resultingly, we have

$$Cov(r_{kt}, \Delta \ln W_{kt}) = s_C \cdot Cov(r_{kt}, \Delta \ln W_{C,kt}) + (1 - s_C) \cdot Var(r_{kt})$$

Hence, even if the cash wage is independent of the stock returns, we will see a positive covariance of overall wage growth to stock returns. In other words, as long as cash wages respond less than 1-for-1 with stock returns, using the latter as an instrument will lead to a downwards bias of the estimated labor supply elasticity and an upwards bias of β:

$$\hat{\beta}_{IV} = s_C \cdot \beta + (1 - s_C) \cdot \frac{Var(r_{kt})}{Cov(r_{kt}, \Delta \ln \ell_{kt})}.$$

Example 3: Fixed value. Finally, suppose workers are promised a fixed compensation in terms of stock values, e.g. 20k USD in form of the firm's shares, such that

$$s = \frac{\mathbb{E}_{t-1}[s_{kt} \cdot V_{kt}]}{\mathbb{E}_{t-1}[s_{kt} \cdot V_{kt}] + \mathbb{E}_{t-1}[W_{C,kt}]}. \tag{A.22}$$

Since $\Delta \ln s_{kt} + \Delta \ln V_{kt}$ is predetermined, it is independent of the stock return. Then, we have that the estimated IV coefficient is given by

$$\hat{\beta}_{IV} = s_C \cdot \beta,$$

which is smaller than the true coefficient. Thus, using stock market returns leads to a downwards biased estimated for β and an upwards biased labor supply elasticity in this case.

A.3 Materials in R&D

Consider the alternative innovation production function with materials R_{kt}.

$$M_{kt+1} = Q_t \cdot A_k \cdot \left(\alpha_L^{\frac{1}{\sigma}} \cdot \ell_{kt}^{\frac{\sigma-1}{\sigma}} + (1-\alpha_L)^{\frac{1}{\sigma}} \cdot \left(\frac{R_{kt}}{Q_t} \right)^{\frac{\sigma-1}{\sigma}} \right)^{\gamma \cdot \frac{\sigma}{\sigma-1}} \tag{A.23}$$

Here, $\alpha_L = 1$ recovers the baseline.

Consumption is then given by

$$C_t = Y_t - X_t - \int_0^1 R_{kt} \cdot dk \tag{A.24}$$

Relative demand for inputs is given by

$$\frac{r_{kt}}{\ell_{kt}} = \left(\frac{1-\alpha_L}{\alpha_L} \right) \cdot ((1+\epsilon_{kt}) \cdot w_{kt})^{\sigma} \tag{A.25}$$

Defining the effective price of R&D input as $P_{R,t} = (\alpha_L \cdot ((1+\epsilon_{it}) \cdot w_{it})^{1-\sigma} + (1-\alpha_L))^{\frac{1}{1-\sigma}}$, firms' first order conditions are given by

$$\ell_{kt} = \underbrace{\alpha_L \cdot \left(\frac{w_{it} \cdot (1+\epsilon_{it})}{P_{R,t}} \right)^{-\sigma}}_{\textit{relative demand effect}} \cdot \underbrace{\left(\frac{\gamma \cdot A_k \cdot \mathbb{E}[z_{kt+1}|z_{kt}]}{P_{R,t}} \right)^{\frac{1}{1-\gamma}}}_{\textit{total demand effect}} \tag{A.26}$$

Two additional parameters to calibrate: α_L and σ. Set σ to standard value in the literature (below 1 appears natural here) and target cost-share of R&D expenditure for α_L.

Bias due to materials. Let $\tilde{w}_{kt} = (w_{kt} \cdot l_{kt} + r_{kt})/\ell_{kt}$, then one can show that

$$\frac{\partial \ln \tilde{w}_{kt}}{\partial \ln \ell_{kt}} = \frac{\partial \ln w_{kt}}{\partial \ln \ell_{kt}} + \underbrace{\frac{r_{kt}}{l_{kt} \cdot w_{kt} + r_{kt}} \cdot \frac{\partial \ln \left((1+\epsilon_{kt})^{\sigma} \cdot w_{kt}^{\sigma-1} \right)}{\partial \ln \ell_{kt}}}_{=bias} \tag{A.27}$$

Thus, the estimated elasticity is going to be biased, however, the direction and extend is ex-ante unclear. Note that the first term of the bias is the expenditure share of materials such that the bias will be small in absolute value of the materials share in cost is small as well.

A.4 Quantitative Model

This Appendix introduces the full quantitative model and derives the key Balanced Growth Path equations.

A.4.1 Setup

There are two types of firms: listed and non-listed. The firms operate identically, but differ in their average productivity as described above.

Final Production. A representative firm hires production labor $L_{P,t}$ at wage $W_{P,t}$ and buys intermediate inputs $\{x_{jt}\}_{j\in[0,Q_t]}$ at price p_{jt} to produce output Y_t. The firm solves

$$\max_{L_{P,t},\{x_{jt}\}_{j\in\mathcal{Q}_t}} Y_t - W_{P,t}\cdot L_{P,t} - \int_{\mathcal{Q}_t} p_{jt}\cdot x_{jt}dj \quad \text{s.t.} \quad Y_t = L_{P,t}^{1-\alpha}\int_{\mathcal{Q}_t} z_{jt}^{1-\alpha}\cdot x_{jt}^{\alpha}dj, \tag{A.28}$$

where z_{jt} is a demand-shifter. Production worker and intermediate good demand is given by

$$\frac{W_{P,t}}{C_t} = \frac{Y_t}{C_t}\cdot\frac{1-\alpha}{L_{P,t}} \quad \text{and} \quad p_{jt} = \alpha\cdot\left(\frac{L_{P,t}\cdot z_{jt}}{x_{jt}}\right)^{1-\alpha}. \tag{A.29}$$

Intermediate good producers. Intermediate goods in the economy can either be protected or unprotected. Protected goods $\mathcal{Q}_t^N$ are propitiatory to a unit mass of intermediate good firms and constant unit cost ψ. For each intermediate good, the proprietor solves

$$\max_{x_{jt}} \quad p_{jt}\cdot x_{jt} - \psi\cdot x_{jt} \tag{A.30}$$

subject to the product demand curve detailed above. Profit maximizing monopoly price p_M is constant across firms and given by $p_M = \frac{\psi}{\alpha}$. Unprotected goods $\mathcal{Q}_t^O$ are produced and sold at unit cost ψ. All prices are relative to the final good whose price is normalized to 1.

Equilibrium quantities x_{kt} for protected and unprotected goods are given by

$$x_{kt} = \begin{cases} z_{kt}\cdot L_{P,t}\cdot\left(\frac{\psi}{\alpha}\right)^{-\frac{1}{1-\alpha}} & \text{if} \quad k\in\mathcal{Q}_t^O \\ z_{kt}\cdot L_{P,t}\cdot\left(\frac{\psi}{\alpha^2}\right)^{-\frac{1}{1-\alpha}} & \text{if} \quad k\in\mathcal{Q}_t^N \end{cases} \tag{A.31}$$

Equilibrium profits for protected products are given by

$$\pi_{kt} = \tilde{\pi}_t\cdot z_{kt} \quad \text{with} \quad \tilde{\pi}_t = (1-\alpha)\cdot\alpha^{\frac{\alpha}{1-\alpha}}\cdot\left(\frac{\alpha}{\psi}\right)^{-\frac{1}{1-\alpha}}\cdot L_{P,t} \quad \text{for} \quad k\in\mathcal{Q}_t^N. \tag{A.32}$$

Products loose protection status with probability δ each period such that

$$\mathcal{Q}^O_{t+1} = \mathcal{Q}^O_t + \delta \cdot \mathcal{Q}^N_t. \tag{A.33}$$

It will be useful to define $Q^N_t = \int_{\mathcal{Q}^N_t} z_{kt} \cdot dk$ and $Q^O_t = \int_{\mathcal{Q}^O_t} z_{kt} \cdot dk$ as the quality adjusted mass of protected and unprotected products, and Q_t as their sum. I will denote values normalized by Q_t in lower case.

The final output can be used for three purposes: consumption, production of intermediate goods and material in innovation. Market clearing thus requires

$$Y_t = C_t + \int_{\mathcal{Q}_t} \psi \cdot x_{jt} \cdot dj + \int_0^1 R_{kt} \cdot dk. \tag{A.34}$$

In a competitive equilibrium, output net of production cost for intermediate goods is

$$Y_t - I_t = Q_t \cdot L_{P,t} \cdot \left((1-\alpha) \cdot q^O_t + (1-\alpha^2)\alpha^{\frac{\alpha}{1-\alpha}} \cdot q^N_t\right) \cdot \left(\frac{\alpha}{\psi}\right)^{\frac{\alpha}{1-\alpha}}. \tag{A.35}$$

Workers and Labor Markets A representative household own all firms and provides labor in form of production workers $L_{P,t}$ and research workers $\{\ell_{kt}\}$. The income from production workers, $W_{P,t}$, research workers $W_{R,kt}$, bond holdings $R_t \cdot B_t$, and firm ownership Π_t can either be consumed C_t or invested in a riskless bond B_{t+1}. Flow utility depends on labor supply and consumption and the future is discounted at rate β. The household solves

$$\begin{aligned} \max \quad & \sum_{t=0}^{\infty} \beta^t \left(\log C_t - \frac{\epsilon}{1+\epsilon}\left(\alpha_P \left(\frac{L_{P,t}}{\alpha_P}\right)^{\frac{1+\epsilon}{\epsilon}} + \alpha_R \left(\frac{L_{R,t}}{\alpha_R}\right)^{\frac{1+\epsilon}{\epsilon}}\right)\right) \\ \text{s.t.} \quad & L_{R,t} = \left(\underline{\ell} + \frac{1}{1+\xi}\right)^{-1} \cdot \left(\int_0^1 \ell_{kt} \cdot \left(\underline{\ell} + \frac{1}{1+\xi}\left(\frac{\ell_{kt}}{L_{R,t}}\right)^{\xi}\right) dk\right) \\ & B_{t+1} + C_t = R_t \cdot B_t + W_{P,t} \cdot L_{P,t} + \int_0^1 W_{R,kt} \cdot \ell_{kt} dk + \Pi_t \end{aligned} \tag{A.36}$$

Household optimization yields standard Euler equation:

$$\frac{C_{t+1}}{C_t} = \beta \cdot R_{t+1}. \tag{A.37}$$

Supply of production labor satisfies

$$\frac{W_{P,t}}{C_t} = \left(\frac{L_{P,t}}{\alpha_P}\right)^{\frac{1}{\epsilon}}. \tag{A.38}$$

Supply for research labor satisfies

$$\frac{W_{R,kt}}{C_t} = \left(\frac{L_{R,t}}{\alpha_R}\right)^{\frac{1}{\epsilon}} \cdot \left(\underline{\ell} + \frac{1}{1+\xi} + \frac{\xi}{1+\xi} \cdot \int_0^1 \left(\frac{\ell_{kt}}{L_{R,t}}\right)^{1+\xi} dk\right)^{-1} \cdot \left(\underline{\ell} + \left(\frac{\ell_{kt}}{L_{R,t}}\right)^{\xi}\right) \tag{A.39}$$

Innovation. Intermediate goods firms hire R&D resouces to produce new blueprints in the subsequent period, which are added to their existing stock. A fraction ζ of firms is "listed" with potentially different levels of R&D productivity across listed and non-listed firms. Otherwise, both firm types behave identically.

Firms hire R&D workers ℓ_{kt} and use materials R_{kt} to produce M_{kt+1} new products in the next period according to production function

$$M_{kt+1} = Q_t \cdot A_k \cdot \left(\alpha_L^{\frac{1}{\nu}} \left(\frac{\ell_{kt}}{\alpha_L}\right)^{\frac{\nu-1}{\nu}} + (1-\alpha_L)^{\frac{1}{\nu}} \left(\frac{R_{kt}}{Q_t}\right)^{\frac{\nu-1}{\nu}}\right)^{\frac{\nu}{\nu-1}\cdot\gamma}. \tag{A.40}$$

Listed and non-listed firms differ exclusively in their level of A_k. Wages are determined in the labor market as detailed above. Materials are produced 1-for-1 from the final output and priced at cost.

Firms' existing protected products lose protection status with probability $\delta_{kt+1} \overset{i.i.d.}{\sim} \mathcal{U}[\underline{\delta}, \bar{\delta}]$, where $\delta = \mathbb{E}[\delta_{kt+1}]$. The quality-adjusted stock of protected products Q^N_{kt} evolves according to

$$Q^N_{kt+1} = M_{kt+1} \cdot z_{kt+1} + (1-\delta_{kt+1}) \cdot Q^N_{kt}. \tag{A.41}$$

The demand-shifter z_{kt+1} is determined at the point of invention and is identical to all products that were invented by the same firm in the same period.[24] It follows a persistent, stochastic process:

$$\ln z_{kt+1} = (1-\rho)\cdot\mu + \rho \cdot \ln z_{kt} + \sigma \cdot \nu_{kt+1} \quad \text{with} \quad \nu_{kt+1} \overset{i.i.d.}{\sim} N(0,1). \tag{A.42}$$

[24] Alternatively, one could assume that demand for all products fluctuates concurrently at the firm level. Such an assumption will affect the precise algebra of the model, but not the qualitative or quantitative properties of the model with respect to the innovation model.

The firm solves

$$V_{kt}(z_{kt}, Q^N_{kt}) = \max_{\ell_{kt}} \left\{ \int_{\mathcal{Q}^N_{kt}} \pi_{kt} \cdot dk - W_{R,kt} \cdot \ell_{kt} - R_{kt} + \frac{1}{R_{t+1}} \cdot \mathbb{E}_t \left[V_{kt+1}(z_{kt+1}, Q^N_{kt+1}) | z_{kt} \right] \right\}$$
$$\text{s.t.} \quad M_{kt+1} = Q_t \cdot A_k \cdot \left(\alpha_L^{\frac{1}{\nu}} \left(\frac{\ell_{kt}}{\alpha_L} \right)^{\frac{\nu-1}{\nu}} + (1-\alpha_L)^{\frac{1}{\nu}} \left(\frac{R_{kt}}{Q_t} \right)^{\frac{\nu-1}{\nu}} \right)^{\frac{\nu}{\nu-1}\cdot\gamma},$$
$$W_{R,kt} = \mathcal{W}_t(\ell_{kt}), \quad \text{and} \quad Q^N_{kt+1} = M_{kt+1} \cdot z_{kt+1} + (1-\delta_{kt+1}) \cdot Q^N_{kt}. \tag{A.43}$$

Lemma 1. *The firm's value function can be decomposed as* $V_{kt}(z_{kt}, Q^N_{kt}) = V_t(z_{kt}, A_k) + V^Q_t \cdot Q^N_{kt}$*, where the* V^Q_t *is the solution to*

$$V^Q_t = \tilde{\pi}_t + \frac{1-\delta}{R_{t+1}} \cdot V^Q_{t+1} \qquad \textit{with} \quad \tilde{\pi}_t \equiv (1-\alpha) \cdot \alpha^{\frac{\alpha}{1-\alpha}} \cdot \left(\frac{\alpha}{\psi} \right)^{-\frac{1}{1-\alpha}} \cdot L_{P,t} \tag{A.44}$$

and $V_{kt}(z_{kt})$ *is the solution to*

$$V_t(z_{kt}, A_k) = \max_{\ell_{kt}} \left\{ -W_{kt} \cdot \ell_{kt} - R_{kt} + \frac{1}{R_{t+1}} \cdot \mathbb{E}_t \left[M_{kt+1} \cdot z_{kt+1} \cdot V^Q_{t+1} + V_{t+1}(z_{kt+1}, A_k) | z_{kt} \right] \right\}. \tag{A.45}$$

The firm's innovation choice problem is thus given by

$$\max_{M_{kt+1}} \quad R^{-1}_{t+1} \cdot \mathbb{E}_t[z_{kt+1}|z_{kt}] \cdot M_{kt+1} \cdot V^Q_{t+1} - W_{R,kt} \cdot \ell_{kt} \qquad \text{s.t.} \quad M_{kt+1} = Q_t \cdot A_k \cdot \ell^{\gamma}_{kt}, \tag{A.46}$$

where the firm takes into account research labor supply and A_k differs across listed and non-listed firms such that listed firms tend to be more productive. Note that this assumption is isomorphic to assuming that these firms have consistently higher product demand.

The aggregate state of technology evolves according to

$$Q_{t+1} = Q_t + \int_0^1 M_{kt+1} \cdot z_{kt+1} \cdot dk. \tag{A.47}$$

A.4.2 Steady-State Equations

Along a BGP, we have

$$g = \int m(z, A) \cdot z \cdot dF(z, A). \tag{A.48}$$

$$1 + r = \frac{\beta}{1+g} \tag{A.49}$$

Firms and innovation.

$$V^Q = \left(\frac{1+r}{r+\delta}\right) \cdot \tilde{\pi}. \tag{A.50}$$

$$V(z,A) = -w(z,A) \cdot \ell(z,A) + \frac{1}{1+r}\left(V^Q \cdot m(z,A) \cdot \mathbb{E}[z'|z] + (1+g) \cdot \mathbb{E}[V(z',A)|z]\right) \tag{A.51}$$

$$\ell(z,A) = \left(\frac{\gamma \cdot A}{w(z,A) \cdot (1+\tilde{\epsilon}(z,A))}\right)^{\frac{1}{1-\gamma}}. \tag{A.52}$$

$$\ln z' = (1-\rho) \cdot \mu + \rho \cdot z + \sigma \cdot \nu \quad \text{with} \quad \nu \sim N(0,1). \tag{A.53}$$

Labor market.

$$w(z,A) = w_R \cdot \left(\underline{\ell} + \left(\frac{\ell(z,A)}{L_R}\right)^{\xi}\right) \tag{A.54}$$

$$w_R = c \cdot \left(\frac{L_R}{\alpha_R}\right)^{\frac{1}{\epsilon}} \cdot \left(\underline{\ell} + \frac{1}{1+\xi} + \frac{\xi}{1+\xi} \cdot \int_0^1 \left(\frac{\ell(z,A)}{L_R}\right)^{1+\xi} dF(z,A)\right)^{-1} \tag{A.55}$$

$$\tilde{\epsilon}(z,A) = \xi \cdot \left(\bar{\ell} + \left(\frac{\ell(z,A)}{L_R}\right)^{\xi}\right)^{-1} \cdot \left(\frac{\ell(z,A)}{L_R}\right)^{\xi} \tag{A.56}$$

$$L^R = \left(\bar{\ell} + \frac{1}{1+\xi}\right)^{-1} \cdot \int \ell(z,A) \cdot \left(\bar{\ell} + \frac{1}{1+\xi} \cdot \left(\frac{\ell(z,A)}{L^R}\right)^{\xi}\right) \cdot dF(z,A) \tag{A.57}$$

$$F(z,A) = F(z) \cdot P(A). \tag{A.58}$$

Aggregates. Composition of products:

$$q^N = \frac{g}{\delta+g} \quad \text{and} \quad q^D = \frac{\delta}{\delta+g}. \tag{A.59}$$

Normalized output and consumption are thus given by

$$c = \left((1-\alpha) \cdot q^O + (1-\alpha^2) \cdot \alpha^{\frac{\alpha}{1-\alpha}} \cdot q^N\right) \cdot \left(\frac{\alpha}{\psi}\right)^{\frac{\alpha}{1-\alpha}} \cdot L_P \tag{A.60}$$

$$y = \left(q^O + \alpha^{\frac{\alpha}{1-\alpha}} \cdot q^N\right) \cdot \left(\frac{\alpha}{\psi}\right)^{\frac{\alpha}{1-\alpha}} \cdot L_P. \tag{A.61}$$

$$R = \frac{\beta}{1+g}$$

$$Y = \left(\alpha^{\frac{\alpha}{1-\alpha}} \cdot (1+g)^{-1} + \alpha^{\frac{2\alpha}{1-\alpha}} \cdot \int_0^1 m_{kt} \cdot z_{kt} dk\right) \cdot \psi^{-\frac{\alpha}{1-\alpha}} \cdot L_P$$

$$C = \left((1-\alpha) \cdot \alpha^{\frac{\alpha}{1-\alpha}} \cdot (1+g)^{-1} + (1-\alpha^2)\alpha^{\frac{2\alpha}{1-\alpha}} \cdot \int_0^1 m_{kt} \cdot z_{kt} dk\right) \cdot \psi^{-\frac{\alpha}{1-\alpha}} \cdot L_P$$

$$\pi_{kt} = (1-\alpha) \cdot \alpha^{\frac{1+\alpha}{1-\alpha}} \cdot \psi^{-\frac{1}{1-\alpha}} \cdot L_P \cdot z_{kt}$$

$$L_P = \left(\frac{Y}{C} \cdot (1-\alpha)\right)^{\frac{\epsilon}{1+\epsilon}} \cdot \alpha^{\frac{1}{1+\epsilon}}$$

$$w_{R,kt} = C \cdot \left(\frac{L_R}{\alpha_R}\right)^{\frac{1}{\epsilon}} \cdot \left(\underline{\ell} + \frac{1}{1+\xi} + \frac{\xi}{1+\xi} \cdot \int_0^1 \left(\frac{\ell_{kt}}{L_R}\right)^{1+\xi} dk\right)^{-1} \cdot \left(\underline{\ell} + \left(\frac{\ell_{kt}}{L_R}\right)^{\xi}\right)$$

$$L_R = \left(\bar{\ell} + \frac{1}{1+\xi}\right)^{-1}$$

$$g = \int_0^1 m_{kt} \cdot dk$$

A.5 Extensions

A.5.1 Human Capital Dynamics

Consider an alternative specification of labor disutility:

$$L_{R,t} = \left(\underline{\ell} + \frac{\int_0^1 \theta_{kt}^{-1} \cdot dk}{1+\xi}\right)^{-1} \cdot \left(\int_0^1 \int_0^1 \ell_{kt} \cdot \left(\underline{\ell} + \frac{\theta_{kt}^{-1}}{1+\xi} \left(\frac{\ell_{kt}}{L_{R,t}}\right)^{\xi}\right) dk\right) \tag{A.62}$$

where θ_{kt} follows law of motion

$$\ln \theta_{kt+1} = \eta \cdot \ln \ell_{kt} + (1-\delta) \cdot \ln \theta_{kt}. \tag{A.63}$$

Here, $\eta = 0$ recovers the baseline model, while $\eta > 0$ allows for some dynamics.

A.5.2 Entry

Formulation in terms of final goods. Free entry conditions requires

$$\mathbb{E}[V_{it}] = \phi_E \cdot M_t^{\varphi}, \tag{A.64}$$

where larger values of φ make M_t less responsive. One can parametrize ϕ_E to ensure that $M_t = 1$ in baseline. Resource costs of entry are given by $\phi_E \cdot M_t$.

In terms of research labor One can augment the utility function such that flow utility is given by

$$\log C_t - \frac{\epsilon}{1+\epsilon}\left(\alpha_P\left(\frac{L_{P,t}}{\alpha_P}\right)^{1+\epsilon}\epsilon + \alpha_R\left(\frac{L_{R,t}+\zeta M_t}{\alpha_R}\right)^{1+\epsilon}\epsilon\right) \tag{A.65}$$

$$\zeta \cdot W_{R,t} \cdot M_t^{\varphi} = \mathbb{E}[V_{it}] \tag{A.66}$$

This formulation allows R&D labor demand by larger firms to crowd out entrepreneurship.

One can implement this formulation in the baseline model by setting $\zeta = \mathbb{E}[V_{it}]/W_{R,t}$ and replacing the original α_R with $\tilde{\alpha}_R = (1 + 1/L_R) \cdot \alpha_R$.

A.5.3 Price discrimination

As mentioned in the beginning of Section 2, the inability of firms to have discriminatory wages among its employees is crucial to generating monopsony power. This section considers the case of wage discrimination and highlights the challenges of disentangling it from monopsony power empirically.

First, note that we can write the labor disutility for R&D workers equivalently as

$$L_{R,t} = \left(\bar{\ell} + \frac{1}{1+\xi}\right) \cdot \int_0^1 \left(\int_0^{\ell_{kt}} \left(\bar{\ell} + \left(\frac{\ell}{L_{R,t}}\right)^{\xi}\right) \cdot d\ell\right) \cdot dk, \tag{A.67}$$

which highlights that the marginal disutility differs among the employees of a given firm. Tracing-out the integral we see that the 0th workers has a disutility proportional to $\bar{\ell}$, while the ℓ_{kt}-th worker has a disutility proportional to $\bar{\ell} + (\ell_{kt}/L_{R,t})^{\xi}$. If a firm can impose perfectly discriminatory wage, then it will pay a lower wage to the former than to the latter. Resultingly, the wage for the ℓth worker at any company needs to satisfy

$$\frac{W_{R,t}(\ell)}{C_t} = \left(\frac{L_{R,t}}{\alpha_R}\right)^{\frac{1}{\epsilon}} \cdot \left(\bar{\ell} + \frac{1}{1+\xi} + \frac{\xi}{1+\xi} \cdot \int_0^1 \left(\frac{\ell_{kt}}{L_{R,t}}\right)^{1+\xi} dk\right)^{-1} \cdot \left(\bar{\ell} + \left(\frac{\ell}{L_{R,t}}\right)^{\xi}\right). \tag{A.68}$$

Total labor cost for the firm, C_{kt}, is then just the intregral over all employees, and marginal cost is the wage of the last employee:

$$C_{kt} = \int_0^{\ell_{kt}} W_{R,t}(\ell) \cdot d\ell \propto \bar{\ell} + \frac{1}{1+\xi} \cdot \left(\frac{\ell_{kt}}{L_{R,t}}\right)^{\xi} \quad \text{with} \quad \frac{\partial C_{kt}}{\partial \ell_{kt}} \propto \bar{\ell} + \left(\frac{\ell_{kt}}{L_{R,t}}\right)^{\xi}. \tag{A.69}$$

Resultingly, firms' marginal costs are the true marginal costs of hiring the last worker and there is no monopsony power. Hence, planner and competitive equilibrium agree on the relative marginal cost of R&D workers across firms and, thus, there is no misallocation of R&D workers across firms nor insufficient demand due to firms' gaming of the labor market.

A natural question is then whether we can distinguish between both models empirically. Unfortunately, this task is difficult as average wages behave quite similarly in both models. In particular, one can verify that the elasticity of the average wage with respect to employment, $W_{kt} = C_{kt}/\ell_{kt}$, remains positive even though firms do not have market power:

$$\frac{\partial \ln W_{kt}}{\partial \ln \ell_{kt}} = \xi \cdot \frac{\frac{1}{1+\xi} \cdot \left(\frac{\ell_{kt}}{L_{R,t}}\right)^{\xi}}{\bar{\ell} + \frac{1}{1+\xi} \cdot \left(\frac{\ell_{kt}}{L_{R,t}}\right)^{\xi}}. \tag{A.70}$$

This phenomenon occurs as rising wages at the margin also push up the average wage, even though inframarginal wages are unaffected. The true differentiating feature of both models is the behavior of inframarginal wages. In the case of monopsony power, all workers are paid the same and, thus, inframarginal wages move as marginal wages. In contrast, inframarginal wages are unaffected by movements in total employment under wage discrimination and, thus, their behavior is disconnected from movements in marginal wages.

In practice, firms are likely to have some power to wage discriminate, but might not be able to achieve full discrimination due to information asymmetries and fairness considerations. It might, thus, be useful to consider a mixture model in which workers are paid partly a common and partly a discriminatory wage. Let α_D be the discriminatory fraction of the wage. Total labor cost are then satisfy

$$C(\ell_{kt}) \propto \ell_{kt} \cdot \left(\bar{\ell} + \frac{1 + (1-\alpha_D) \cdot \xi}{1+\xi} \cdot \left(\frac{\ell_{kt}}{L_{R,t}}\right)^{\xi}\right) \tag{A.71}$$

Resultingly, marginal cost become proportional to

$$\frac{\partial C_{kt}}{\partial \ell_{kt}} \propto \left(1 + (1-\alpha_D) \cdot \xi \cdot \frac{\left(\frac{\ell_{kt}}{L_{R,t}}\right)^{\xi}}{\bar{\ell} + \left(\frac{\ell_{kt}}{L_{R,t}}\right)^{\xi}}\right) \left(\bar{\ell} + \left(\frac{\ell_{kt}}{L_{R,t}}\right)^{\xi}\right) \tag{A.72}$$

Evidently, marginal costs are proportional to marginal disutility for $\alpha_D = 1$ and to marginal average disutility for $\alpha_D = 0$. Note, however, that the elasticity of the average wage with respect to labor remains essentially unaffected:

$$\frac{\partial \ln C(\ell_{kt})/\ell_{kt}}{\partial \ln \ell_{kt}} = \xi \cdot \frac{\frac{1+(1-\alpha)\cdot\xi}{1+\xi} \cdot \left(\frac{\ell_{kt}}{L_{R,t}}\right)^{\xi}}{\bar{\ell} + \frac{1+(1-\alpha)\cdot\xi}{1+\xi} \cdot \left(\frac{\ell_{kt}}{L_{R,t}}\right)^{\xi}} \tag{A.73}$$

Finally, one tell-tale sign of wage discrimination are, naturally, wage differences. In particular, one can show that the absolute differences in (relative) wages within a firm is a direct function of the degree of price discrimination:

$$\frac{1}{\ell_{lk}} \int_0^{\ell_{kt}} \left(\frac{|W_{kt}(\ell, \alpha_D) - W_{kt}|}{W_{kt}} \right) \cdot d\ell = \alpha_D \cdot \frac{2 \cdot \xi}{(1+\xi)^{2+\xi}} \cdot \frac{\left(\frac{\ell_{kt}}{L_{R,t}}\right)^{\xi}}{\bar{\ell} + \frac{1+(1-\alpha_D)}{1+\xi} \left(\frac{\ell_{kt}}{L_{R,t}}\right)^{\xi}}, \tag{A.74}$$

where $W_{kt}(\ell) = \alpha_D \cdot W_t(\ell) + (1-\alpha_D) \cdot W_t(\ell_{kt})$ is the mixture of the discriminatory and non-discriminatory wage paid to workers.

A.6 Depreciation shocks

Assume instead of complete depreciation that inventions only become publicly available with probability $\delta \sim U[\underline{\delta}, \bar{\delta}]$ and otherwise remain linked to the firm.

Version 1: Permanent productivity. Assume that the z value of an invention is permanent based on the period of invention and define Q^N as the quality-adjusted stock of inventions of a firm, which evolves according to

$$Q^N_{kt+1} = M_{kt+1} \cdot z_{kt+1} + (1 - \delta_{kt+1}) \cdot Q^N_{kt}. \tag{A.75}$$

Normalized by Q_t, we have

$$(1+g) \cdot q^N_{kt+1} = m_{kt+1} \cdot z_{kt+1} + q^N_{kt}. \tag{A.76}$$

I will denote the value of owning a stock $\tilde{Q}_{kt}$ at the beginning and end of period at $V^Q(\tilde{Q}_{kt})$ and P^Q_{kt} respectively. The value of owning an existing stock at the end of period is then given by the solution to

$$P^Q_t(\tilde{Q}_{kt}) = \frac{1}{R_{t+1}} \mathbb{E}\left[\pi \cdot (1 - \delta_{kt+1}) \cdot \tilde{Q}_t + P^Q_{t+1}((1 - \delta_{kt+1}) \cdot \tilde{Q}_{kt})\right], \tag{A.77}$$

where π are profits per unit of quality. Guessing and verifying that $P^Q_t(\tilde{Q}_{kt}) = P^Q \cdot \tilde{Q}_{kt}$, we have

$$P^Q = \left(\frac{1-\mathbb{E}[\delta]}{r+\mathbb{E}[\delta]}\right)\cdot\pi \qquad \text{and} \qquad V^Q = \frac{1+r}{r+\mathbb{E}[\delta]}. \tag{A.78}$$

The return on owning such as stock is the given by

$$R^Q_{t+1} = \frac{V^Q\cdot\tilde{Q}_{kt}\cdot(1-\delta_{kt+1})}{P^Q\cdot\tilde{Q}_{kt}} = (1+r)\cdot\frac{1-\delta_{kt+1}}{1-\mathbb{E}[\delta]} \tag{A.79}$$

Denote by $V^Z_t(z)$ and $P^Z_t(z)$ the value of innovation capacity. The former is the solution to

$$\begin{aligned} V^Z_t(z) &= \max\left\{-\ell_{kt}\cdot W_{kt} + \frac{1}{1+r}\mathbb{E}\left[V^Q\cdot M_{kt+1}\cdot z' + V^Z_t(z')|z\right]\right\} \\ s.t.\quad & M_{kt+1} = Q_t\cdot A_k\cdot\ell^{\theta}_{kt} \qquad \text{and} \qquad W_{kt} = \mathcal{W}_t\cdot\left(\bar{\ell}+\left(\ell_{kt}/L^R_t\right)^{\xi}\right) \end{aligned} \tag{A.80}$$

Guessing $V^Z_t(z) = Q_t\cdot V^Z(z)$ along the Balanced Growth Path, we have

$$\begin{aligned} V^Z(z) &= \max\left\{-\ell_{kt}\cdot w_{kt} + \frac{1}{1+r}\mathbb{E}\left[V^Q\cdot m_{kt+1}\cdot(1+g)\cdot z' + V^Z_t(z')|z\right]\right\} \\ s.t.\quad & m_{kt+1} = A_k\cdot\ell^{\theta}_{kt} \qquad \text{and} \qquad w_{kt} = \mathcal{W}\cdot\left(\bar{\ell}+\left(\ell_{kt}/L^R\right)^{\xi}\right) \end{aligned} \tag{A.81}$$

Furthermore, we have

$$P^Z(z) = \mathbb{E}\left[V^Q\cdot m_{kt+1}\cdot(1+g)\cdot z' + V^Z_t(z')|z\right] \tag{A.82}$$

The return on the innovation capacity is thus given by

$$R^Z_{kt+1}(z) = \frac{V^Z(z')}{P^Z(z')} = (1+r)\cdot\frac{V^Q\cdot m_{kt+1}\cdot(1+g)\cdot z' + V^Z_t(z')}{\mathbb{E}\left[V^Q\cdot m_{kt+1}\cdot(1+g)\cdot z' + V^Z_t(z')|z\right]} \tag{A.83}$$

The total return of a firm is then given by

$$R_{kt+1} = \frac{P^Q\cdot\tilde{q}_{kt}}{P^Q\cdot\tilde{q}_{kt}+P^Z(z_{kt})}\cdot R^Q_{kt+1} + \frac{P^Z(z_{kt})\cdot\tilde{q}_{kt}}{P^Q\cdot\tilde{q}_{kt}+P^Z(z_{kt})}\cdot R^Z_{kt+1}. \tag{A.84}$$

I denote quantity of undepreciated and depreciated varieties as Q^N_t and Q^D_t respectively with the LOM:

$$Q^N_{t+1} = \int_0^1 M_{kt+1}\cdot z_{kt+1}\cdot dk + (1-\mathbb{E}[\delta])\cdot Q^N_t \tag{A.85}$$

$$Q^D_{t+1} = \mathbb{E}[\delta]\cdot Q^N_t + Q^D_t \tag{A.86}$$

Furthermore, I will assume that knowledge externalities are linked to $Q_t = Q_t^D + Q_t^N$.

I denote the share of undepreciated varieties as q_N and the share of depreciated quality-adjusted varieties as q_D s.t.

$$q^N = \frac{g}{\delta + g} \quad \text{and} \quad q^D = \frac{\delta}{\delta + g}. \tag{A.87}$$

Normalized output and consumption are thus given by

$$c = \left((1-\alpha) \cdot \alpha^{\frac{\alpha}{1-\alpha}} \cdot q^D + (1-\alpha^2) \cdot \alpha^{\frac{2\alpha}{1-\alpha}} \cdot q^N\right) \cdot \psi^{-\frac{\alpha}{1-\alpha}} \cdot L_P \tag{A.88}$$

$$y = \left(\alpha^{\frac{\alpha}{1-\alpha}} \cdot q^D + \alpha^{\frac{2\alpha}{1-\alpha}} \cdot q^N\right) \cdot \psi^{-\frac{\alpha}{1-\alpha}} \cdot L_P. \tag{A.89}$$

Version 2: Productivity shocks. Alternatively, assume that quality depends entirely on the firm. The mass of inventions a firm has patented evolves according to

$$Q_{kt+1} = M_{kt+1} + (1 - \delta_{kt+1}) Q_{kt}. \tag{A.90}$$

As before, I denote the present discounted value of a mass of goods by $V_t^Q(Q_{kt}, z_{kt})$, which solves

$$V_t^Q(Q_{kt}, z_{kt}) = Q_{kt} \cdot z_{kt} \cdot \pi + \frac{1}{1+r}\mathbb{E}_t\left[V_{t+1}^Q(Q_{kt}(1-\delta_{kt+1}), z_{kt})\right]. \tag{A.91}$$

Guessing and verifying that $V_t^Q(Q_{kt}, z_{kt}) = Q_{kt} \cdot V^Q(z_{kt})$ along the Balanced Growth Path, we have

$$V^Q(z) = z \cdot \pi + \left(\frac{1 - \mathbb{E}[\delta]}{1+r}\right) \cdot \mathbb{E}[V^Q(z')|z]. \tag{A.92}$$

End of period price:

$$P^Q(z) = \left(\frac{1 - \mathbb{E}[\delta]}{1+r}\right) \cdot \mathbb{E}[V^Q(z')|z]. \tag{A.93}$$

Return

$$R_{kt+1}^Q = (1+r) \cdot \frac{1 - \delta_{kt+1}}{1 - \mathbb{E}[\delta]} \cdot \frac{V^Q(z_{kt+1})}{\mathbb{E}_t[V^Q(z_{kt+1}|z_{kt})]} \tag{A.94}$$

The value of innovation

$$\begin{aligned} V_t^Z(z) &= \max\left\{-\ell_{kt} \cdot W_{kt} + \frac{1}{1+r}\left(\mathbb{E}_t[M_{kt+1} \cdot V^Q(z')|z] + \mathbb{E}_t[V_{t+1}^Z(z')|z]\right)\right\} \\ s.t. \quad M_{kt+1} &= Q_t \cdot A_k \cdot \ell_{kt}^\theta \qquad \text{and} \qquad W_{kt} = \mathcal{W}_t \cdot \left(\bar{\ell} + \left(\ell_{kt}/L_t^R\right)^\xi\right) \end{aligned} \tag{A.95}$$

Normalized along the BGP

$$V^Z(z) = \max\left\{-\ell_{kt}\cdot w_{kt} + \frac{1}{1+r}\left(\mathbb{E}_t[m_{kt+1}\cdot V^Q(z')|z] + (1+g)\mathbb{E}_t[V^Z(z')|z]\right)\right\}$$
$$s.t.\quad m_{kt+1} = A_k\cdot \ell_{kt}^{\theta} \qquad \text{and} \qquad w_{kt} = \mathcal{W}\cdot\left(\bar{\ell} + \left(\ell_{kt}/L^R\right)^{\xi}\right) \tag{A.96}$$

End of period price

$$P^Z(z) = \frac{1}{1+r}\left(\mathbb{E}_t[m_{kt+1}\cdot V^Q(z')|z] + (1+g)\mathbb{E}_t[V^Z(z')|z]\right). \tag{A.97}$$

Return

$$R^Z_{kt+1} = (1+r)\cdot\frac{m_{kt+1}\cdot V^Q(z') + (1+g)V^Z(z')}{\mathbb{E}_t[m_{kt+1}\cdot V^Q(z')|z] + (1+g)\mathbb{E}_t[V^Z(z')|z]} \tag{A.98}$$

The total return of a firm is then given by

$$R_{kt+1} = \frac{P^Q\cdot\tilde{q}_{kt}}{P^Q\cdot\tilde{q}_{kt} + P^Z(z_{kt})}\cdot R^Q_{kt+1} + \frac{P^Z(z_{kt})\cdot\tilde{q}_{kt}}{P^Q\cdot\tilde{q}_{kt} + P^Z(z_{kt})}\cdot R^Z_{kt+1}. \tag{A.99}$$

I denote quantity of undepreciated and depreciated varieties as Q^N_t and Q^D_t respectively with the LOM:

$$Q^N_{t+1} = \int_0^1 M_{kt+1}\cdot dk + (1-\mathbb{E}[\delta])\cdot Q^N_t \tag{A.100}$$
$$Q^D_{t+1} = \mathbb{E}[\delta]\cdot Q^N_t + Q^D_t \tag{A.101}$$

Furthermore, I will assume that knowledge externalities are linked to $Q_t = Q^D_t + Q^N_t$.

I denote the share of undepreciated varieties as q_N and the share of depreciated quality-adjusted varieties as q_D s.t.

$$q^N = \frac{g}{\delta+g} \quad \text{and} \quad q^D = \frac{\delta}{\delta+g}. \tag{A.102}$$

Normalized output and consumption are thus given by

$$c = \left((1-\alpha)\cdot\alpha^{\frac{\alpha}{1-\alpha}}\cdot q^D + (1-\alpha^2)\cdot\alpha^{\frac{2\alpha}{1-\alpha}}\cdot q^N\cdot\tilde{z}\right)\cdot\psi^{-\frac{\alpha}{1-\alpha}}\cdot L_P \tag{A.103}$$

$$y = \left(\alpha^{\frac{\alpha}{1-\alpha}}\cdot q^D + \alpha^{\frac{2\alpha}{1-\alpha}}\cdot q^N\cdot\tilde{z}\right)\cdot\psi^{-\frac{\alpha}{1-\alpha}}\cdot L_P. \tag{A.104}$$

where $\tilde{z} = \int_0^1 \frac{q^N_{kt}}{q^N}\cdot z_{kt}dk$. The weights of which, with a change of metric can be computed as the solution to

$$\tilde{q}^N(z') = \left(\frac{\delta + g}{g}\right) \cdot \int P(z'|z) \cdot m(z) \cdot dz + (1 - \delta) \cdot \int P(z'|z) \cdot \tilde{q}^N(z) \cdot dz. \quad \text{(A.105)}$$

Such that

$$\tilde{z} = \int \tilde{q}^N(z) \cdot z \cdot dz \quad \text{(A.106)}$$

A.7 Alternative Calibrations

Table A.1: Parameters and Calibration Targets for Simple Calibration

A. Parameters			
Parameter	Symbol	Value	Source
A.1. External calibration			
Discount factor	β	0.97	Standard value
Labor supply elasticity	ϵ	0.50	Chetty et al. (2012)
R&D scale elasticity	γ	0.50	Acemoglu et al. (2018)
Share of listed firms	ζ	0.05	NSF BRDIS 2019
Markup parameter	α	0.80	Terry (2023)
A.2. Internal calibration			
Labor disutility production	α_P	0.153	Direct
Labor disutility R&D	α_R	0.319	Direct
R&D productivity listed	A_l	0.404	Moment matching
R&D productivity unlisted	A_{nl}	0.014	Moment matching
Std. dev. R&D prod. shocks	σ	0.370	Moment matching
Autocorr. R&D prod. shocks	ρ	0.950	Moment matching
Avg. R&D supply elasticity	ξ	4.042	Moment matching
Rev. R&D supply elasticity	$\bar{\ell}$	$2.35 \cdot 10^4$	Moment matching
B. Moments			
Moment	Data	Model	Source
Growth rate	0.015	0.015	Data
Relative R&D listed vs non-listed	35	35	Data
Std. dev. of R&D growth-rate	0.316	0.316	Data
Autocorr. of R&D	0.922	0.918	Data
Wage elasticity	0.923	0.884	Data
Wage elas. for small R&D	0.41	0.41	Data
Δ wage elas. large R&D	1.245	1.358	Data
R&D employment	0.047	0.047	Acemoglu et al. (2018)
Production employment	0.286	0.286	Acemoglu et al. (2018)

Note: TBD.

B Data Appendix

B.1 Variable Construction

Inventor workforce robustness. I confirm that the pattern observed in Table **??** is driven by true inventors in two robustness exercises. In the first robustness, I restrict the inventors in my sample to those with (1) at least 10 patents in their career, (2) more than 5 years with patent applications, and (3) an at least 10-year gap between the first and last patent application. In the second robustness I further restrict the sample to inventors who worked for at least 2 listed US companies. These restriction put the focus on a robust set of professional inventors with long careers in innovation.

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 **??** for further details on the construction.

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 B for further details on the construction.

C Empirical Appendix

C.1 First-stage Results

Table C.1 reports the first-stage results for the main specification.

Table C.1: 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	$\Delta \ln \texttt{Inventors}_{it}$ × **{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%.

C.2 Robustness for Elasticity Estimates

Table C.2: 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)
— × {Top 50% R&D Return}	1.079**	1.093**		
	(0.512)	(0.517)		
— × {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 × year fixed effects. Standard errors clustered at the NAICS6 level.

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

Table C.3: 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 C.4: 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%.

Online Appendix

Not for publication

D Online Theory Appendix

D.1 Regression Bias with Supply Shocks

Labor supply is given by

$$L_R = \int_0^1 \alpha_{it}^{-1} \ell_{it} \cdot \left(\frac{\ell_{it} \cdot \alpha_{it}^{-1}}{L_R} \right)^{\xi} \cdot di \tag{D.1}$$

Firm-specific labor supply satisfies

$$W_{it} \propto \frac{1}{\alpha_{it}} \cdot \left(\frac{\ell_{it} \cdot \alpha_{it}^{-1}}{L_R} \right)^{\xi} \tag{D.2}$$

Labor demand

$$\gamma \cdot \theta_{it} \cdot \ell_{it}^{\gamma-1} = (1+\xi) \cdot W_{it} \tag{D.3}$$

Equilibrium quantities and wages

$$\ell_{it} \propto \theta_{it}^{\frac{1}{\xi+1-\gamma}} \cdot \alpha_{it}^{\frac{1+\xi}{\xi+1-\gamma}} \quad \text{and} \quad W_{it} \propto \theta_{it}^{\frac{\xi}{\xi+1-\gamma}} \cdot \alpha_{it}^{\frac{(1+\xi)(1-\gamma)}{\xi+1-\gamma}} \tag{D.4}$$

Thus

$$\frac{\Delta \ln W_{it}}{\Delta \ln \ell_{it}} = \xi \cdot \frac{\Delta \ln \theta_{it}}{\Delta \ln \theta_{it} + (1+\xi) \cdot \Delta \ln \alpha_{it}} - (1-\gamma) \cdot \frac{(1+\xi) \cdot \Delta \ln \alpha_{it}}{\Delta \ln \theta_{it} + (1+\xi) \cdot \Delta \ln \alpha_{it}} \tag{D.5}$$

Story 1: Differences in the nature of stock returns. Firms with high level of R&D employment might have stock returns that are more sensitive to demand shocks (e.g. due to existing stock of knowledge) rather than supply shocks, giving them a larger elasticity. They have already build up the portfolio and, thus, are less reliant on generous workers.

Story 2: Differences in compensation schemes. Larger firms might rely more on stock compensation to motivate workers (they do in the data). Thus, their R&D wages are more sensitive to the stock-market for "nefarious" reasons.

E Online Empirical Appendix

E.1 Calculating the Labor Share in R&D

I calculate the labor share in R&D for the US in 2000 and 2019 using the “All industries” data reported in the 2000 Survey of Industrial Research and Development (SIRD), which was conducted by the Division of Science Resources Statistics within the National Science Foundation (NSF), and the 2019 Business Enterprise Research and Development Survey (BERDS), which was conducted by the National Center for Science and Engineering Statistics (NCSES) and Census Bureau. In both cases, I first calculate the attributable R&D costs, which excludes undefined costs and includes imputed opportunity cost for capital, and then report the share of labor costs thereof. For the 2000 figures I make a range of adjustment to capture costs that are reported in detail in 2019, but lumped into an "Other" category in 2000. These adjustments are based on the 2019 values reported for these categories and detailed in the footnotes of Table E.1.

As reported in Table E.1, the labor share of attributable R&D costs was 79% in 2019 and 70% in 2000 yielding an average of 74.5%. The remainder of the costs is split between “materials and equipment” and capital, where the former tends to be more important. Notably, the labor share in R&D costs is significantly higher than the labor share in the US overall, which is typically reported around 67% [ADD CITATION HERE]. Hence, R&D is a very labor intensive task, justifying the focus on labor markets in R&D.

Table E.1: National Labor Share in R&D

	2000	2019
A. Raw R&D costs [% thereof]		
Raw R&D cost	199.5	493.0
R&D wages and benefits	84.2 [42.2%]	268.0 [54.4%]
Stock-based compensation	12.3 [6.1%]*	39.0 [7.9%]
Temporary staffing	6.7 [3.4%]*	21.4 [4.3%]
Materials and supplies	28.1 [14.1%]	34.4 [7.0%]
Royalties and licensing fees	3.7 [1.9%]*	9.2 [1.9%]
Expensed equipment	2.9 [1.5%]*	7.2 [1.5%]
Lease and rental payments	3.3 [1.7%]*	8.2 [1.7%]
Depreciation	4.0 [2.0%]	18.9 [3.8%]
Other	54.2 [27.2%]*	86.6 [17.6%]
B. Attributable R&D cost		
Raw R&D costs	199.5	493.0
– Other	- 54.2	- 86.6
+ Imputed cost of capital	2.0	9.4
Attributable R&D costs	147.3	415.8
C. Attributable costs shares [% thereof]		
Materials and equipment	34.8 [23.6%]	50.9 [12.2%]
Capital	9.3 [6.3%]	36.5 [8.8%]
Labor	103.2 [70.1%]	328.4 [79.0%]

Notes: Values in Panel A are taken from the source noted in the text except those market with *, which are imputed. Labor related values are imputed to keep constant their relative size to R&D wages and benefits. Other values are imputed to keep constant their relative size to overall R&D. Finally, the "Other" category is adjusted such that the individual items add up to raw R&D cost. Panel B calculates attributable R&D costs as raw R&D cost minus other cost plus cost of capital. The latter are imputed as 50% of depreciation, which is in line with an interest rate of 7.5% and depreciation rate of 15%. The final panel categorizes R&D costs into materials and equipment, capital, and labor. Materials and equipment includes materials and supplies, royalties and licensing fees, and expensed equipment. Capital includes depreciation, lease and rental payments, and imputed cost of capital. Labor includes R&D wages and benefits, stock-based compensation, and temporary staffing.