Does Monopsony Matter for Innovation?*

Nils H. Lehr†

International Monetary Fund

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Abstract

This paper examines how firms' monopsony power—their ability to depress wages by restricting employment—in the market for inventors affects U.S. innovation and economic growth. Using an instrumental variable strategy, I estimate firm-level inventor labor supply elasticities and find that firms face less than perfectly elastic supply, with larger employers wielding greater monopsony power. I develop and quantify a heterogeneous firms growth model with size-dependent monopsony power that matches this evidence. The model suggests that monopsony power reduces annual U.S. economic growth by 0.20 percentage points and welfare by 11% through depressed R&D employment and misallocation.

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†Email: nilslehr@bu.edu

1 Introduction

The growing dominance of large firms has fostered an active debate on its origins and impact on the U.S. economy (Grullon et al., 2019; Autor et al., 2020). Politicians, commentators, and academics alike have raised concerns that rising concentration may be closely linked to a perceived decline in competition and rise in firms' market power (Wu, 2018; Philippon, 2019; Meagher, 2020). Concerns about insufficient competition increasingly include labor markets where large firms may have the power to suppress the wages of their employees. For example, labor markets are explicitly mentioned in the White House's 2021 executive order on "Promoting Competition in the American Economy" and they are at the core of the revised 2023 Horizontal Merger Guidelines, which were informed by the recent monopsony literature (The White House, 2021; Berger et al., 2023).

Labor market power, commonly referred to as monopsony power, was considered most prevalent for "low-skilled" workers in rural communities, e.g., for miners in towns with only few coal mines in close proximity, however, recent evidence suggests that it extends to "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).

Building on these findings, I study the macroeconomic consequences of monopsony power over inventors, a group of highly specialized workers with an outsized impact on productivity and growth. Monopsony power may be both particularly widespread and concerning for inventors, since their skills tend to be highly specialized and their output, i.e., inventions, is considered one of the key drivers of long-run economic growth and welfare. Furthermore, the compounding nature of innovation implies that monopsony among innovators may have important dynamic implications that go beyond static inefficiencies. 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 it would not enforce non-compete agreements (The Department of Justice, 2010; Reuters, 2022).

This paper estimates that monopsony power in the market for corporate inventors has a sizable negative impact on innovation and economic growth. I find that 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 in larger employers. Quantitatively, my results indicate that monopsony power over inventors reduces long-run economic growth by 0.20 p.p. leading to welfare loss of 11% compared to a world in which firms act as price takers.

I reach these conclusions in three steps. First, I introduce monopsony power over inventors into a simple endogenous growth model with heterogeneous firms. Inventors choose their employer based on idiosyncratic preference shocks and wages offered as in Card et al. (2018). As a result, firms face an upwards sloping labor supply curve and can lower wages marginally without losing 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 and 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. I confirm robustness using firm-level productivity shocks from Imrohoroglu and Tuzel (2014).

My estimates suggests that monopsony power is both sizable and size-dependent. I estimate an average inverse labor supply elasticity of 0.44, which implies that a firm would lose about 23% 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 their local labor market. Importantly, I find that firms with above median R&D workforce face an inverse labor supply elasticity of 0.75 compared to approximately 0 for smaller firms. Thus, firms with above median inventor employment would lose only about 13% of their R&D workforce if they were to reduce their wages by 10%, while below median R&D employment firm have no wage setting power and face a perfectly competitive labor market. Similarly, the literature on production workers finds that larger employers face less elastic labor supply and, thus, have more monopsony power. 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 and calibrate it by moment matching using the evidence on the labor supply elasticity of inventors. The calibrated model is then used as a laboratory to study the impact of monopsony in the market for corporate inventors on innovation and economic growth. I introduce three extensions that account for important structural features of the R&D sector. 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 1.70% per year—leading to a 11% welfare improvement. The acceleration in economic growth is driven both by a 2% 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 18 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 in the market of corporate inventors and linking size-dependent monopsony power to R&D investments and, thus, economic growth. 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. This group is crucial due to its close link to R&D investments, which in turn are commonly identified as a main driver of long-run productivity growth in the U.S. My model builds on the literature microfounding monopsony power via preferences over employers. 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 and estimating that tackling monopsony power could significantly accelerate U.S. economic growth. 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., 2024; 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.Interestingly, this mechanism 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, 2024). 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 (2024), 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.

2 A Growth Model with Monopsony over Inventors

This section introduces preference-based monopsony power 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. The model is simplified to emphasize the main insights and will be extended in Section 4 to introduce elements that may shape the model's quantitative predictions in a full calibration.

2.1 Model Description and Decentralized Equilibrium

Time is discrete and indexed by t. The economy is populated by a representative household that supplies production and research labor and allocates its income between consumption and savings. The final good is produced by a representative firm from producton labor and intermediate inputs. The latter are produced by a unit mass of profit-maximizing research firms that own their exclusive production rights. In turn, research firms hire researchers and materials to invent new types of intermediate goods.

Workers and Labor Markets. There is a representative household with King-Plosser-Rebelo preferences over consumption C_t and labor supply for production $L_{P,t}$ and R&D $L_{R,t}$ represented by flow utility function $U(C_t, L_{P,t}, L_{R,t})$ (King et al., 1988):

$$\begin{aligned} U(C_t, L_{P,t}, L_{R,t}) &= \frac{(C_t \cdot v(L_{P,t}, L_{R,t}))^{1-\sigma} - 1}{1-\sigma} \\ \text{with} \quad v(L_{P,t}, L_{R,t}) &= \exp\left(-\frac{\epsilon}{1+\epsilon}\left(\alpha_P^{-\frac{1}{\epsilon}} \cdot L_{P,t}^{\frac{1+\epsilon}{\epsilon}} + \alpha_R^{-\frac{1}{\epsilon}} \cdot L_{R,t}^{\frac{1+\epsilon}{\epsilon}}\right)\right) \end{aligned} \tag{1}$$

The parameter σ controls the intertemporal elasticity of substitution, while ϵ determines the aggregate labor supply elasticity. The preference parameters α_P and α_R shift the supply of production and research labor. The preferences are chosen to allow for a balanced growth path with constant labor supply and steady consumption growth. The structure of labor disutility is such that labor supply of both types is independent, which allows for a separation of the production and R&D sectors. 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.

Labor supply for researchers itself is potentially differentiated, which captures the idea that firms are imperfect substitutes from the perspective of workers due to e.g. differential amenities, management styles, company cultures or visions. I denote the supply of researchers for firm $k \in [0,1]$ by ℓ_{kt} and total labor supply $L_{R,t}$ is given by aggregator

$$L_{R,t} = \left(\underline{\ell} + \frac{1}{1+\xi}\right)^{-1} \cdot \left(\int_0^1 \int_{\ell_{kt}} \left(\underline{\ell} + \left(\frac{\ell}{L_{R,t}}\right)^{\xi}\right) d\ell \cdot dk\right) \quad \text{with} \quad \xi \geq 0. \tag{2}$$

The aggregator integrates over firms as well as over workers within firms, where the marginal disutility for is increasing in the number of workers hired as long as $\xi > 0$. This formulation captures the idea that workers have idiosyncratic preferences over employers such that firms hiring more researchers face ever less enthusiastic workers at the margin. As long as $\bar{\ell} = 0$, the aggregator is of the CES-type and, thus, has a constant elasticity with respect to labor supply for an individual firm. For $\bar{\ell} > 0$, the aggregator is non-homothetic with a rising elasticity with respect to ℓ_{kt} such that larger employers face more inelastic R&D labor supply. Solving the inner level of aggregation, we have

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

From this formulation, we can immediately see that scaling by $L_{R,t}$ on the right-hand side ensures that proportional shifts in ℓ_{kt} across all firms map 1-for-1 into $L_{R,t}$.

The household receives income from three sources: labor supply, firm ownership, and bond holdings. Production workers are paid common wage $W_{P,t}$, while researchers are paid firm-specific wages $W_{R,kt}$. Bonds holdings B_t earn gross interest R_{t+1} in the subsequent period and firm ownership yields profits Π_t. The household owns all firms.

Note that I do not allow firms to pay discriminate wages across researchers, but instead force them to pay a single firm-level wage. Labor supply then implies that the wage is set such that it compensates the last hired researcher for their labor supply. This assumption is crucial to generating monopsony power in this model as firms take into account that they have to pay inframarginal researchers higher wages to attract additional researchers at the margin. I discuss the implication of price discrimination in the discussion section.

Finally, the household allocates income across consumption C_t and riskless bond holdings B_t, which are in 0 net-supply and earn gross return R_{t+1} in the following period. The budget constraint is thus given by

$$B_{t+1} + C_t = R_t \cdot B_t + W_{P,t} \cdot L_{P,t} + \int_0^1 W_{R,kt} \cdot \ell_{kt} \cdot dk + \Pi_t. \tag{3}$$

The household discounts the future at rate $\beta < 1$ and the combined probem is given by

$$\max_{\{C_t, L_{P,t}, \{\ell_{kt}\}_{k\in[0,1]}\}} \sum_{t=0}^{\infty} \beta^t \cdot U(C_t, L_{P,t}, L_{R,t}) \quad \text{s.t. (1), (2), and (3).} \tag{4}$$

Final Production. A representative firm hires production labor $L_{P,t}$ and buys intermediate inputs $\{x_{jt}\}_{j\in\mathcal{Q}_t}$ to produce output Y_t with production function

$$Y_t = L_{P,t}^{1-\alpha} \int_{\mathcal{Q}_t} z_{jt}^{1-\alpha} \cdot x_{jt}^{\alpha} dj, \tag{5}$$

where z_{jt} is a demand-shifter for intermediate inputs. The firm takes as given the wage $W_{P,t}$ and intermediate input prices p_{jt} and maximizes its profits:

$$\max_{L_{P,t},\{x_{jt}\}_{j\in\mathcal{Q}_t}} Y_t - W_{P,t} \cdot L_{P,t} - \int_{\mathcal{Q}_t} p_{jt} \cdot x_{jt} dj \quad \text{s.t. } (5). \tag{6}$$

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 in terms of the final good. For each intermediate good, the proprietor solves

$$\pi_{jt} = \max_{x_{jt}} \quad p_{jt} \cdot x_{jt} - \psi \cdot x_{jt} \tag{7}$$

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

$$M_{kt+1} = Q_t \cdot A_k \cdot \ell_{kt}^{\gamma}, \tag{8}$$

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

$$Q_{kt+1} = M_{kt+1} \cdot z_{kt+1} + Q_{kt}. \tag{9}$$

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.[1] Firms'

[1]Alternatively, one could assume that demand for all products fluctuates concurrently at the firm

demand-shifter is persistent and evolves according to

$$\ln z_{kt+1} = (1-\rho)\cdot\mu + \rho\cdot\ln z_{kt} + \sigma\cdot\nu_{kt+1} \quad \text{with} \quad \nu_{kt+1} \sim N(0,1). \tag{10}$$

Intermediate firms hire researchers to maximize their value

$$V_t(Q_{kt}, z_{kt}) = \max_{\ell_{kt}} \left\{ \int_{j\in Q_{kt}} \pi_{jt}\cdot dj - W_{kt}\cdot\ell_{kt} + R_{t+1}^{-1}\cdot\mathbb{E}_t\left[V_{t+1}(z_{kt+1}, Q_{kt+1})|z_{kt}\right] \right\} \tag{11}$$

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

$$Q_{t+1} = Q_t + \int_0^1 M_{kt+1}\cdot z_{kt+1}\cdot dk. \tag{12}$$

Market Clearing. Labor market clearing is implicit in the household setup such that the only remaining market that needs to be cleared is the product market, which requires:

$$Y_t = C_t + \psi\cdot\int_{Q_t} x_{jt}\cdot dj \tag{13}$$

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

Definition 1 (Decentralized Balanced Growth Path Equilibrium)**.** *A sequence of quantities and prices such that (a) households maximize utility by solving* (4)*, (b) firms maximize profits by solving* (6) *and* (7)*, and firm value by solving* (11)*, (c) markets clear* (13)*, (d) quantities grow at a constant rate* $g = Q_{t+1}/Q_t - 1$*, except for labor supply, which remains constant at the aggregate level.*

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.

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:

$$\begin{aligned} \max \quad & \sum_{t=0}^{\infty} \beta^t \cdot U(C_t, L_{P,t}, L_{R,t}) \text{ s.t. } (1), (2), (5), (10), (13), \text{ and} \\ & Q_{t+1}/Q_t - 1 = \int_0^1 A_k \cdot z_{kt+1} \cdot \ell_{kt}^{\gamma} \cdot dk \end{aligned} \tag{14}$$

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* (14) *such that productivity* Q_t *grows at a constant rate* g*.*

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. Furthermore, this sensitivity is stronger for firms that are already larger when $\bar{\ell} > 0$, i.e., in the case of log-concave labor supply. Resultingly, firms' demand for R&D workers becomes less sensitive to R&D productivity shocks or targeted subsidies as they get larger.

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 decentralized 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 decentralized equilibrium as the sensitivity of wages changes alongside the wages or marginal products themselves, which is only taken into account by profit maximizing firms.

Derivations and proofs are provided in Appendix B.

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*

$$\left.\frac{\partial \ln W_{R,kt}}{\partial \ln \ell_{kt}}\right|_{\Delta\tau_{kt}} = \xi \cdot \frac{(\ell_{kt}/L_{R,t})^{\xi}}{\bar{\ell} + (\ell_{kt}/L_{R,t})^{\xi}}, \tag{15}$$

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 decentralized equilibrium as long as $\bar{\ell} = 0$ and becomes less sensitive in the case of $\bar{\ell} > 0$ as inventor employment increases.

Proposition 2 highlights two effects of monopsony power on equilibrium R&D employment. 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 decentralized equilibrium features insufficient R&D due to an insufficient market size, which is linked to the monopoly distortion in the product market, and intertemporal knowledge externalities. Monopsony power thus further increases this gap. Secondly, with log-concave labor supply, the relative allocation of R&D workers in the decentralized 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 (Efficiency in the R&D sector)**.** *Denote quantities in the Decentralized and Planner equilibria by superscripts and suppose $\bar{\ell} = 0$, i.e., labor market power is homogeneous. Then, employment of R&D workers is insufficient in the decentralized equilibrium ($L^D_{R,t} < L^P_{R,t}$), however, their relative allocation across firms is efficient, i.e., $\ell^D_{kt}/\ell^D_{mt} = \ell^P_{kt}/\ell^P_{mt}\ \forall k, m$. The efficient equilibrium can be achieved with untargeted output and R&D subsidies. Conversely, suppose that the aggregate level of R&D workers is fixed, i.e. $\epsilon \to 0$, then R&D employment 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 decentralized equilibrium is inefficiently tilted towards smaller firms, i.e.,* $\ell^D_{kt}/\ell^D_{mt} < \ell^P_{kt}/\ell^P_{mt}$ *if* $\ell^D_{kt} > \ell^D_{mt}$*. 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 the recent literature arguing that large firms might invest too much in R&D relative to small firms (Aghion et al., 2024; de Ridder, 2024). Both views are easily reconciled when considering the source of heterogeneity in innovation activity. In my model, heterogeneity is driven by productivity differences across firms that a planner would also consider when allocating R&D workers. In contrast, differences in R&D activity across firms in the aforementioned papers are driven by heterogeneity in the ability to profit from innovation, which leads large firms to do too much R&D relative to a planner, who would not factor in firms' ability to charge higher markups when deciding on the allocation of R&D resources. In practice, both forces might be partly offsetting with ambiguous net effects. This paper focuses on quantifying the effect of monopsony power only.

Finally, there are tell-tale signs of monopsony in the model that do not require estimating the labor supply elasticity. In particular, the R&D return, or the ratio of R&D output to its costs, is an increasing function of firms' R&D employment if and only if there is size-dependent monopsony power, as shown in Proposition 3. Intuitively, firms with more monopsony power are able to achieve higher R&D output relative to R&D costs by supressing wages. The link between monopsony power and R&D employment then extends to the R&D returns. In contrast, if firms acted as price takers, they would equalize wages to marginal products of R&D workers and, thus, also equalize R&D returns at a common value. Finding a positive correlation between R&D returns and R&D employment is thus a potentially strong signal of size-dependent monopsony power.

Proposition 3. *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*

$$\textit{Expected R\&D Return}_{kt} \equiv \frac{M_{kt+1} \cdot \mathbb{E}_t[z_{kt+1}|z_{kt}] \cdot \tilde{\pi}_{t+1}/R_{t+1}}{W_{R,kt} \cdot \ell_{kt}} = \frac{1}{\gamma} \cdot (1 + 1/\epsilon_{kt}). \quad (16)$$

It is constant across firms if and only if $\bar{\ell} = 0$ *and increasing in* ℓ_{kt} *for* $\ell_{kt} > 0$. *The 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. Using firm-level data is key in my context since the firm-level elasticity of labor supply is different from the market-level elasticity in the model presented above. As formally shown in Proposition 4 in the Appendix, market level variation in R&D wages and employment can only identify the aggregate R&D labor supply elasticity ϵ, rather than the parameters of the firm-level R&D labor supply elasticity $\{\xi, \bar{\ell}\}$. Intuitively, individual firms can expand R&D employment by hiring from competitors or by hiring from non-employment. However, if all firms expand, then only the latter option is feasible, leading to a potentially different labor supply elasticity.

I obtain financial data from WRDS Compustat, who collect and harmonize them based on mandatory filings by the company. The data extend 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 patent in the year prior to the application. I then 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. I construct three additional measures using a full-time equivalent approach, only inventors located in the US, or focusing on the inventors identified by Kaltenberg et al. (2021). I similarly create a measure on inventor productivity using lifetime patenting measures and calculate average inventor productivity at a firm using the appropriate averages. See Appendix A.1 for additional details.

I measure inventor wages as the ratio of R&D expenditure divided by inventor employment. 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.[2] 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 result 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:

$$\text{R\&D Return}_{it} \equiv \frac{\sum_{s=0}^{4} \text{Patent Valuations}_{it+s}}{\sum_{s=0}^{4} \text{R\&D Expenditure}_{it-1+s}}. \tag{17}$$

I also construct measures of firms' dominance in their technology markets and inventor specialization, which are described in the text and Appendix A.1.

I restrict the sample to 1975-2014 and drop firms with consistently low R&D expenditures (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 A.1 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

[2] 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%. See Online Appendix C.1.

regressing log changes in the inventor wage on changes in log inventor employment as shown in equation (18) (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. Running the regression in differences has the benefit of accounting for long-run differences in levels. In my baseline, I select $t-2$ as reference period and investigate the change up to $t+3$. I also provide results for alternative horizons k.

$$\Delta_k \ln \text{Inventor Wage}_{it} = \bar{\epsilon}_k \times \Delta_k \ln \text{Inventors}_{it} + \alpha_{j(i)\times t} + \varepsilon_{it} \tag{18}$$

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 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 summary, 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 in $t-1$ as an instrument for changes in inventor employment, which follows Seegmiller (2023)'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 wage growth other than through their impact inventors employment growth. As a robustness check, I also present results using firm-level TFP shock constructed from Imrohoroglu and Tuzel (2014).

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.

$$
\begin{aligned}
\Delta \ln \text{Inv. Wage}_{it} = \quad & \epsilon_l \times \Delta \ln \text{Inv.}_{it} \\
& + (\epsilon_h - \epsilon_l) \times \Delta \ln \text{Inv.}_{it} \times \{\text{Above Median Inventors}\}_{it} \\
& + \beta\{\text{Above Median Inventors}\}_{it} + \alpha_{j(i)\times t} + \varepsilon_{it}
\end{aligned} \tag{19}
$$

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.[3] 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.[4] 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.[5] However, this is only a concern if the incentive pay is structured such that stock market returns affect the level of compensation. Note also that I investigate differences in R&D wages between $t+3$ and $t-2$ and instrument using returns in $t-1$. Thus, my estimation should be robust if bonuses are one-off and are paid out in $t-1$ or t.[6] Incentive pay could also bias estimate of the interaction regression, e.g., if firms with larger R&D employment rely more on it.[7] 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 instru-

[3] 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.

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

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

[6] 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 B.3.

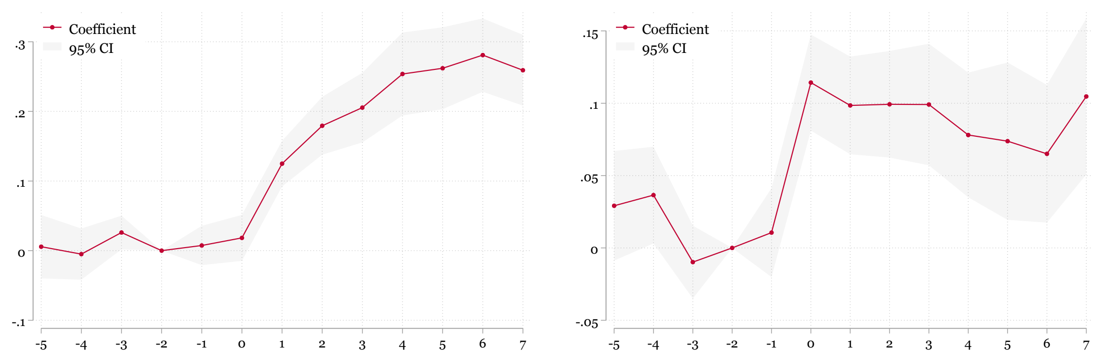
[7] Data from the NSF suggests that larger firms, as measured by total employment, do rely more on incentive pay, however, the difference is quantitatively small.

ment.[8] I consider this threat together with incentive pay explicitly when quantifying the aggregate implications of R&D monopsony power.

3.3 First-stage and Reduced Form

I report the first stage results in Panel A of Figure 1. Stock market returns are associated with a significant subsequent expansion of inventor employment. The baseline estimate ($t = 3$) suggests that a 10% increase in the firm valuation is associated with a 2% expansion of R&D employment. The estimate is highly statistically significant and has an associated F-statistic comfortably above the commonly referenced threshold of 10. R&D employment rises gradually over time, echoing estimates for regular workers in Seegmiller (2023).

Figure 1: First Stage and Reduced Form Estimates



A. R&D Employment B. R&D Wage

Panel B reports the reduced-form estimate confirming that stock market returns are significantly associated with rising R&D wages. The baseline estimate suggests that a 10% increase in firm value is associated with a 1% rise in R&D wages. Combining first-stage and reduced-form estimates implies an average labor supply elasticity around $1\%/2\% \approx 0.5$.

[8]I discuss this issue in detail in Appendix B.5. The bias depends, among other things, on the elasticity of substitution between materials and inventors.

3.4 Second Stage Results

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 4.4% higher wages. For comparison, Seegmiller (2023) estimates a slightly larger elasticity of 0.84 for high-skilled workers using LEHD data on wages and employment. The estimated elasticity suggests that workers receive about $1/(1 + 0.437) \approx 70\%$ of their marginal product in wages. Second, the heterogeneity analysis across firm-size suggests that this effect is coming exclusively from firms with a large inventor workforce. A firm with above median inventors faces an elasticity of about 0.75 implying that a 10% increase in employment requires 7.5% larger wages, while there is no significant impact on smaller firms. These estimates suggest that inventors working for large innovative firms receive 57% of their marginal product in wages, while R&D workers at small innovative firms receive their entire marginal product.[9] Third, column (3) reveals that firms with large R&D return also face less elastic inventor supply, as predicted by the model. Quantitatively, the estimates are closely aligned with the results for inventor employment. Remaining differences may be due to the fact that R&D returns are a noisy measure of labor market power as they reflect all frictions faced by the firm. In summary, the evidence suggests that smaller firms face competitive labor markets for inventors, while larger firms have some monopsony power.

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 including them as control variables in my regression.[10] The associated regression results, as reported in Appendix Table A.4, suggest that inventor quality is positively associated with inventor wages, however, this relationship does not quantitatively alter the estimated inventor supply elasticities.

[9] These estimates do not imply that wage levels are larger for smaller R&D employers as marginal products may differ substantially.

[10] 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.

Table 1: Inverse R&D Labor Supply Elasticity Estimates

	(1)	(2)	(3)
		R&D Wage Growth	
R&D Employment Growth	0.437***	-0.039	0.012
	(0.150)	(0.120)	(0.158)
— × Above Median R&D Employment		0.746***	
		(0.201)	
— × Above Median R&D Return			0.647***
			(0.186)
First stage F stat. (Main)	67	39	31
First stage F stat. (Inter.)	–	30	95
Observations	12,772	12,772	12,772

Note: R&D employment and wage growth are log differences between $t-2$ and $t+3$. R&D employment growth is instrumented for with stock market returns in $t-1$. All regressions control for NAICS3 × year fixed effects. F statistics reported are based on Sanderson and Windmeijer (2015). Standard errors are clustered at the NAICS6 level.

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

Second, I control for pre-trends by adding lagged employment and wage growth as in Seegmiller (2023), which does not significantly change estimated coefficients as reported in Appendix Table A.2. Third, I explore robustness with respect to the measure of inventors in Appendix Table A.1 and find essentially identical estimates when alternatively using (1) a full-time equivalent measure of inventors, (2) only US inventors, or (3) only verified inventors as identified by Kaltenberg et al. (2021). Finally, I find quantitatively larger estimates when using TFP shocks instead of stock market returns as instrument, however, the estimates are less precise due to a weaker first stage. Nonetheless a similar pattern emerges, confirming that large firms or those with high returns have monopsony power.

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 introduced in Section 2 that is calibrated to match the evidence.

4.1 Quantitative Model

There are at least three challenges in using the model presented in Section 2 together with the evidence in Section 3 to investigate the economic impact of monopsony power in R&D. First, my sample is restricted to listed firms, which tend to be larger. Consequently, I might overstate the importance of monopsony power by using evidence on large firms, which have more monopsony power according to the evidence presented above, while ignoring the 40% of R&D expenditure accounted for by smaller firms.[11] Second, the model ignores non-labor inputs in R&D, which account for 20% of R&D expenditure in practice (see Appendix C.1). As I discuss below, introducing intermediate inputs dampens the impact of monopsony power as firms can substitute them for R&D workers. Finally, the model abstracts from pay linked to firm performance such as stock-based compensation, which may bias estimated firm-level labor supply elasticities.[12]

To address these challenges, I extend the baseline model along three dimensions. 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 and, thus, R&D employment. As a result, adding these firms to the model introduces a mass of firms with relatively low monopsony power, as long as $\bar{\ell} > 0$, which reduces its overall impact 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 in the form of a fixed number of stocks in the next period that is set to constitute a constant share of expected wages. The number of shares is set one period in advance such that workers at fortunate firms receive an unexpected pay increase. Consequently, a fraction of the realized wage is directly linked to stock market returns for the firm, which, as discussed above, constitutes a violation of the exclusion

[11]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%.

[12]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.

restriction for using stock market returns as an instrument for R&D productivity shocks when estimating the inverse labor supply elasticity. [13] 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:

$$M_{kt+1} = Q_t \cdot A_k \cdot \left(\alpha_L^{\frac{1}{\theta}} \cdot \ell_{kt}^{\frac{\theta-1}{\theta}} + (1-\alpha_L)^{\frac{1}{\theta}} \cdot \left(\frac{R_{kt}}{Q_t} \right)^{\frac{\theta-1}{\theta}} \right)^{\gamma \cdot \frac{\theta}{\theta-1}}. \tag{20}$$

The new production function 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:

$$Y_t = C_t + \int_0^1 x_{kt} \cdot dk + \int_0^1 R_{kt} \cdot dk. \tag{21}$$

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 includes materials and machinery. I show in Appendix B.5 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, this bias can be accounted for within the model.

[13] To give a numerical example, consider workers at a firm have an expected wage of 0.5 tomorrow and expect the firm to have value 1.5. The stock-based compensation is set such that workers expect to earn 15% of their salary through stock-based compensation. Then, workers will receive $\frac{15\% \cdot 0.5}{1.5} = 0.05$ shares of the firm tomorrow. Suppose that wages are fixed, however, the firm's value 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, while they receive $1 \cdot 0.05 + 0.85 \cdot 0.5 = 0.475$ if the value goes down. This mechanism, thus, yields a positive correlation between stock returns and compensation even though expected wages are constant.

4.2 Calibration

I parameterize the quantitative model using a combination of external and internal calibration.[14] 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 set the R&D scale elasticity to $\gamma = 0.5$ as in Acemoglu et al. (2018) and calibrate the demand parameter α to achieve a markup $(1/\alpha)$ 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 to $\theta = 0.5$, which is in line with the estimates for the production sector in Oberfield and Raval (2021).[15] Finally, I set the share of listed firms to 5% based on the firms in my sample compared to the NSF R&D surveys.[16]

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 $\{A_{nl}, A_l\}$. 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.[17] 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

[14]See Appendix B.2 for a full description of the quantitative model together with the (recursive) balanced growth path equilibrium. Additional details on calibration and simulation are also presented there.

[15]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.

[16]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.

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

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. At last, I target the regression evidence in columns (1) and (2) of Table 1 to inform the monopsony parameters $\{\xi, \bar{\ell}\}$.

Table 2 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 wage elasticity for small firms, which the model overestimates.

The model makes a range of predictions for the R&D returns under monopsony power as discussed in Proposition 3. I confirm these in Table 3, which reports empirical estimates in Column (1) and coefficients based on simulated data in Column (2). I investigate two predictions that were not exploited in the calibration and that can be thought of as untargeted moments. First, the model predicts a positive correlation between inventor employment and R&D returns as long as there is size-dependent monopsony power. Indeed, I find a strong positive correlation in the data in Panel A and a highly similar coefficient in the calibrated model.[18] In the data, a 10% increase in inventor employment is associated with a 2.5% higher R&D returns, while the calibrate model predicts a 2.2% larger return. Second, the model predicts that shocks inducing firms to hire more inventors should also be correlated with larger R&D returns. Indeed, panels B and C confirm that stock market returns as well as productivity growth is positively correlated with R&D returns in the data and the model, with estimates of similar magnitude. Finally, note that the model cannot account for these pattern if firms effectively act as price takers, i.e., in absence of size-dependent monopsony power, as R&D returns are a constant in that case.

Finally, I confirm in Appendix B.6 that the calibration would overstate the degree of monopsony power if I did not account for materials in R&D and stock-based compensation.

[18] I also find in Appendix Table A.5 that the correlation between R&D returns and inventors is robust to controlling for overall employment, which does not predict returns conditional on R&D employment.

Table 2: Parameters and Calibration Targets for Main Calibration

A. Parameters			
Parameter	Symbol	Value	Source
A.1. External calibration			
Discount factor	β	0.96	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 non-listed firms	ζ	0.05	NSF BRDIS 2019
Markup parameter	α	0.80	Terry (2023)
Elas. of substitution in R&D	θ	0.50	Oberfield and Raval (2021)
A.2. Internal calibration			
Labor disutility production	α_P	0.205	Direct
Labor disutility R&D	α_R	0.121	Direct
Labor weight in R&D	α_L	0.968	Direct
R&D productivity listed	A_l	0.261	Moment matching
R&D productivity unlisted	A_{nl}	0.014	Moment matching
Std. dev. R&D prod. shocks	σ	0.238	Moment matching
Autocorr. R&D prod. shocks	ρ	0.985	Moment matching
Avg. R&D supply elasticity	$\underline{\xi}$	1.922	Moment matching
Rel. R&D supply elasticity	$\bar{\ell}$	57.3	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	0.923	Data
Wage elasticity	0.437	0.436	Data
Wage elas. for small R&D	0	0.201	Data
Δ wage elas. large R&D	0.746	0.747	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)

Notes: This table reports calibrated parameter values and targeted moments in the data and model. Panel A reports parameter values distinguishing between externally calibrated parameters in Panel A.1 and internally calibrated parameters in Panel A.2. Panel B reports the targeted moments from the data and the model values from the calibration. See text for additional details.

Table 3: R&D Returns and Monopsony

	(1)	(2)
A. Inventors	ln **R&D Return**	
ln Inventors	0.253***	0.221***
	(0.031)	(0.000)
B. Stock Market Return	ln **R&D Return**	
Lagged Excess Return	0.258***	0.250***
	(0.031)	(0.004)
C. Productivity growth	ln **R&D Return**	
Lagged TFP Growth	0.220***	0.111***
	(0.044)	(0.003)
Source	Data	Model
Monopsony	—	Yes
Observations	7,931	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 A for details. Standard errors are clustered at the NAICS6 level.

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

4.3 Counterfactuals

Table 4 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 through offsetting subsidies such that firms effectively act as price takers in the R&D labor market. The "Fixed $\tilde{L}_R$" scenario induces firms to act as price takers, but holds constant total R&D employment $\tilde{L}_R = \int_0^1 \ell_{kt} \cdot dk$ through an untargeted R&D tax. Thus, this scenario focuses exclusively on the impact of reallocating R&D employment across firms. Finally, scenario $\Delta\tilde{L}_R$ leaves monopsony power in place but implements the aggregate R&D employment of the "Full" counterfactual through an R&D subsidy. This scenario, thus, quantifies the impact of lower aggregate demand for R&D workers compared to a no-monopsony world.[19]

[19] As discussed in Section 2, the competitive demand for R&D workers need not be socially optimal due to the standard externalities involved in R&D.

Table 4: Counterfactuals for Main Calibration

Outcome	Baseline	No Monopsony		
		Full	Fixed $\tilde{L}_R$	$\Delta\ \tilde{L}_R$
A. Aggregates				
Growth rate	1.50%	1.70%	1.68%	1.51%
Δ Welfare	0.0%	10.6%	10.3%	0.3%
Δ R&D Employment	0.0%	1.9%	0.0%	1.9%
Δ Firm Value	0.0%	13.6%	13.4%	0.2%
B. R&D Employment Share				
Top 10%	68.0%	81.2%	81.2%	68.0%
Top 5%	48.6%	64.6%	64.7%	48.6%
Top 2.5%	34.5%	49.5%	49.5%	34.4%
C. Wage Premium				
Top 10%	21.4%	14.7%	14.7%	21.4%
Top 5%	45.4%	34.0%	33.9%	45.4%
Top 2.5%	76.6%	61.2%	61.1%	76.6%

Notes: This table reports counterfactuals for offsetting monopsony power through targeted subsidies. The first and second columns report the calibration and counterfactual without entry. The third column report the counterfactual holding constant the number of employed researchers. The last column instead considers a counterfactual with targeted subsidies, but where the aggregate employment of researchers conforms with the no monopsony counterfactual. See text for additional details.

Table 4 reveals substantial economic costs of monopsony power. In its absence, growth accelerates from 1.5% per annum to 1.7%—a 13% increase—yielding a 11% welfare improvement in consumption equivalent terms. These effects are comparable to other market distortions: Berger et al. (2022) estimate that monopsony power in the production sector reduces output by 21% and welfare by 7.6%, while Aghion et al. (2024) estimate that resolving static and dynamic misallocation from heterogeneous product market power across firms would boost economic growth by 31% with a welfare improvement of 9%. Similarly, de Ridder (2024) finds that changes in business dynamism induced by rising fixed costs reduced economic growth by 23% and welfare by 9%. Thus, labor market power in the R&D sector is sizable and about equally harmful as monopsony in the production sector and misallocation due to markups.

Faster growth in the counterfactual stems from rising R&D employment and a more efficient R&D allocation. Column (3) shows that, holding constant aggregate R&D hours, inducing the efficient allocation improves growth by 0.18 p.p. and welfare by 10.3%. In turn, I find in column (4) that shifting only aggregate R&D employment boosts growth by 0.01 p.p. and welfare by 0.3%. Thus, misallocation alone accounts for about 0.18 p.p./0.20 p.p. = 90% of the cost of monopsony in R&D. As shown in Panel B, the model without monopsony power features significantly more concentrated R&D employment. For example, the share of R&D expenditure accounted for by the 2.5% largest firms rises from 35% to 50%. Intuitively, rising monopsony power at the top held back their demand for R&D resources, such that the decentralized equilibrium features more concentration. Nonetheless, wage premia at the top fall slightly, as shown in Panel C, due to a general rise in R&D wages in the middle of the R&D employment distribution.

5 Robustness and Discussion

Next, I discuss various robustness checks and investigate potential concerns with the main analysis. I report the alternative calibrations and counterfactuals in Tables B.2–B.4.

Perfect price discrimination. The model assumes that firms cannot price discriminate among their workers, which is necessary to generate monopsony power.[20] I relax this assumption in Appendix B.4.2 by introducing a flexible level of price discrimination. While higher levels of price discrimination reduce the growth impact of monopsony power, the effects remain large at intermediate levels. Re-estimating the model assuming an intermediate level of price discrimination, I find that offsetting the remaining monopsony power improves growth by 0.12 p.p. and welfare by 6.3% (see column (6)). Thus, monopsony continues to be costly in terms of growth and welfare even at intermediate levels of price discrimination.

Firm entry and entrepreneurship. Another important consideration is firm

[20] This assumption could be tested with inventor-level data by investigating 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.

entry and entrepreneurship. The exercise of monopsony power increases the value of the firms and, thus, might incentivize entry. However, using subsidies to incentivize firms to (implicitly) ignore their monopsony power increases their value even further as reported in row four of Table 4. We might thus suspect that this leads to additional entry, which further boosts innovation. I propose a model extension with entry in Appendix B.4.1 and calibrate it to match the baseline model under monopsony. Column (7) in Table B.3 then investigates the implication of offsetting monopsony power through subsidies under free entry. I find that monopsony is even more costly in this scenario. Inducing firms to be price takers through subsidies increases the number of active firms by 22% and improves growth by 0.48 p.p. and welfare by 20%.

Financing subsidies. The counterfactual implicitly assumes that R&D subsidies are financed in a manner that does not influence firms' incentives to innovate, e.g., through lumpsum taxation of households. Alternatively, one may consider a sophisticated R&D tax scheme that induces an efficient allocation across firms while breaking even. I investigate this option in Panel B of Table B.3 and find that it would reduce growth slightly and improve welfare by less than the baseline. Intuitively, the tax scheme requires a large subsidy for firms conducting a lot of R&D, which requires heavy taxes on average to break even. These taxes are so large that average R&D employment falls by about 20% in the main calibration resulting in a reduction of growth by 0.01 p.p.. On net, the scheme boosts welfare by 6.7% as lower labor disutility outweighs the minor growth deceleration. Interestingly, such a scheme remains growth improving under free entry. This occurs as free entry yields a reduction in the number of R&D workers per firm and, thus, less monopsony power even at the top. Consequently, less tax revenue is needed and, thus, fewer disincentives created on average.

Calibration robustness. I conduct a range of additional robustness exercises around the model calibration. In the first set of exercises, I re-calibrate the model under alternative assumptions about exogenous parameters and the mechanics of bonus payments. First, I consider a specification where R&D employment and materials are substitutes by recalibrating the model with $\theta = 1.5$. Second, I consider two alternative incentive pay schemes. In the first scheme, I assume that the stock compensation distributed depends on the current rather than expected future wage. In the second scheme, I instead assume that workers are simply paid a bonus whenever the firm achieves positive stock market returns. Finally, I also consider the simple case without material inputs and stock compensation. For these models, I find that offsetting monopsony power improves growth by 14–19 p.p. and welfare by 7–12%.

In the second set of robustness exercises, I explore the model's estimated impact of monopsony power for alternative calibrations in which I vary parameters around their estimated values. As reported in Table B.4, increasing the dispersion of R&D productivity—either by raising the variance σ^2 or autocorrelation ρ of R&D productivity shocks or by decreasing the relative productivity of unlisted firms A_{nl}/A_l—raises the welfare benefits of tackling monopsony power. These benefits are not driven by a larger growth impact, however, but by a smaller increase in R&D employment at constant growth impact, i.e., larger gains in aggregate R&D productivity. Raising the average R&D supply elasticity ξ raises the cost of monopsony by raising its impact on growth and R&D employment. A larger relative R&D supply elasticity $\bar{\ell}$ is similarly connected to higher welfare costs of monopsony power, however, the effects are driven by a smaller expansion of R&D employment that compensates a slightly lower growth impact in welfare terms. Finally, raising the labor intensity of R&D predictably, as it raises the welfare costs of monopsony and its growth impact. Jointly, these robustness checks confirm that the counterfactuals are sensitive to the parameterization, however, they are robust around the calibration matching the targeted moments.

Sources of monopsony power. Monopsony power is often associated with a lack of outside options for workers. I provide evidence in favor of this idea in Table A.5 by developing two measures of limited outside options and documenting their relationship to a proxy for monopsony power, R&D returns. First, I develop a measure of firm dominance in its specific inventor labor market, which I define using technology classifications of patents and calculate as the share of inventors employed by the firm among those patenting in the relevant technology classes. Column (5) confirms that this measure is significantly associated with R&D return, in line with a size-dependent monopsony interpretation. Second, a lack of outside options can be the product of specialization on the part of inventors such that firms hiring more specialized inventors tend to have larger R&D returns. 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. I aggregate to the firm level by taking an average over all employed inventors. Column (6) confirms that firms hiring more specialized inventors indeed have larger R&D returns—in line with the idea that they have more market power.

6 Conclusion

Politicians, commentators, and academics alike have raised concerns about the macroeconomic implications of limited competition in U.S. labor markets. This paper suggests that these concerns are warranted when it comes to the market for inventors, who possess highly specialized skills and, thus, potentially limited outside options. The implications are particularly severe as inventors drive productivity growth, and static inefficiencies from monopsony power are compounded by innovation's cumulative nature.

I reach this conclusion in three steps. First, I present a heterogeneous firms endogenous growth model with monopsony power in the inventor market. The model identifies two key channels: monopsony power reduces aggregate inventor employment through wage depression when supply is not perfectly inelastic, and stronger monopsony power among larger firms creates misallocation by shifting inventors toward less productive employers. Second, using an instrumental variable strategy to estimate firm-level inventor labor supply elasticities, I find substantial monopsony power among large firms. While small firms face competitive conditions, larger employers lose only 13% of R&D employment for a 10% wage reduction, paying inventors only two-thirds of their marginal product. Third, I calibrate a quantitative extension of the model to these elasticities, finding that eliminating monopsony power would increase economic growth by 13% and welfare by 11%.

These results suggest at least two avenues for future research. First, monopsony power in the corporate sector might affect inventors' entrepreneurial activity, particularly relevant given big tech firms' extensive startup acquisitions. Second, monopsony power might influence human capital investment by depressing returns and creating differential exposure across skills, affecting both the distribution of inventors across firms, but also of human capital across skills.

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Appendix

A Empirical Appendix

A.1 Variable Construction

R&D Employment. I calcualte R&D employment based on inventors listed on firms' granted patents. I link patents to firms in Compustat using the crosswalk in Kogan et al. (2017) and assign each firm a share of a given inventor in each year based on the share of patents assigned to the firm. I then record total inventor in the year prior to the patent application to reflect the time at which they worked on a given application. Finally, I aggregate to the firm level. In my baseline, I use the inventors identified by USPTO's Patentsview and confirm robustness with those identified by Kaltenberg et al. (2021).

Labor Market Dominance. 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.

Inventor Specialization. I contruct a firm-level proxy for it by aggregating an inventor-level measure of specialization. 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.

R&D Returns. I construct R&D returns as the ratio of patent valuations estimated in Kogan et al. (2017) to R&D expenditure over a 5-year window. I focus on observations with at least 50 underlying patents. See Lehr (2024) for a further discussion of the meassure.

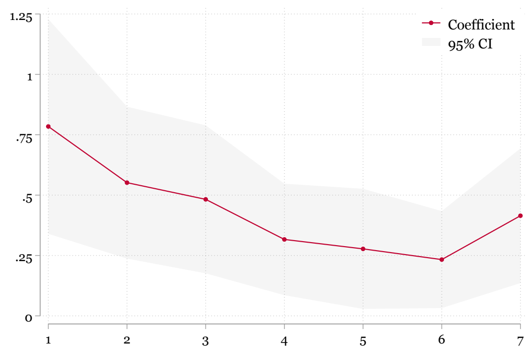
Stock-market returns. I construct annual stock market returns from monthly returns reported in CRSP. I then construct excess returns using the S&P500 index returns from the same data source. When constructing returns, I line up the month with the fiscal year of the company.

A.2 Robustness for Elasticity Estimates

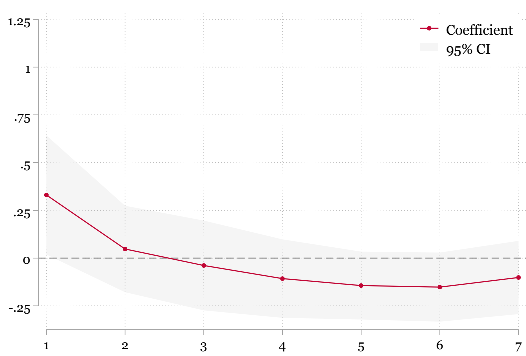
Figure A.1 reports estimates for the average inverse labor supply elasticity (Panel A) as well as the interaction regression (Panel B and C) for different time horizons. The average estimates are decreasing over time starting at about 0.75 and stabilitizing around 0.25 in the long-run. The evidence from the interaction regression highlights that the overall decline in the estimate is driven by below median R&D employment firms, while the estimate for the gap between above and below median R&D employment firms is relatively stable. The estimate for below median R&D employment firm is only significant in $t = 1$ and close to zero in subsequent periods. This finding motivates the focus on the $t = 3$ estimate in the main text.

Additional robustness exercises are reported in Tables A.2 - A.4. Table A.2 adds prior growth rates for R&D employment and wage as controls as in Seegmiller (2023). Table A.1 uses alternative measures of inventor employment. Table A.3 uses TFP growth in $t-1$ constructed from the TFP estimates in Imrohoroglu and Tuzel (2014) as an alternative instrument for R&D employment growth. Finally, A.4 add inventor productivity—measured by the average patents per year of employed inventors—as a control variable. Across robustness exercises I find estimates highly consistent with the main estimates.

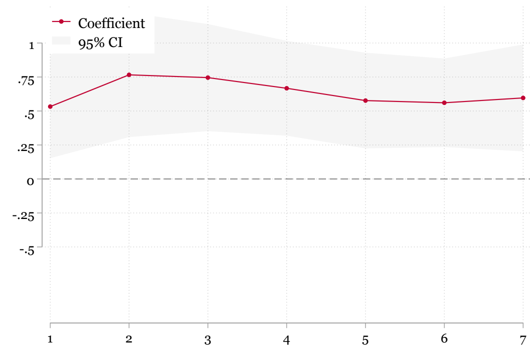
Figure A.1: Elasticity Estimates Over Time



A. Average Effect



B. Low R&D Employment



C. High vs. Low R&D Employment

Table A.1: Inverse R&D Labor Supply Elasticity Estimates — Inventor Robustness

	(1)	(2)	(3)	(4)
A. Baseline		**R&D Wage Growth**		
R&D Employment Growth	0.437***	0.480***	0.436***	0.523***
	(0.150)	(0.157)	(0.150)	(0.175)
First stage F stat. (Main)	67	69	62	53
First stage F stat. (Inter.)	–	–	–	–
Observations	12,772	12,710	12,772	12,563
B. Interaction with Size		**R&D Wage Growth**		
R&D Employment Growth	-0.039	-0.059	-0.046	-0.087
	(0.120)	(0.122)	(0.121)	(0.132)
— × Above Median R&D Employment	0.746***	0.774***	0.749***	0.771***
	(0.201)	(0.199)	(0.201)	(0.201)
First stage F stat. (Main)	39	42	37	35
First stage F stat. (Inter.)	30	33	29	31
Observations	12,772	12,710	12,772	12,563
B. Interaction with Return		**R&D Wage Growth**		
R&D Employment Growth	0.012	0.026	-0.000	-0.007
	(0.158)	(0.167)	(0.159)	(0.194)
— × Above Median R&D Return	0.647***	0.688***	0.652***	0.740***
	(0.186)	(0.198)	(0.188)	(0.228)
Inventor measure	Baseline	US only	FTE	Verified
First stage F stat. (Main)	31	32	29	25
First stage F stat. (Inter.)	95	94	93	72
Observations	12,772	12,710	12,772	12,563

Note: R&D employment and wage growth are log differences between $t-2$ and $t+3$. R&D employment growth is instrumented for with stock market returns in $t-1$. All regressions control for NAICS3 $\times$ year fixed effects. F statistics reported are based on Sanderson and Windmeijer (2015). Standard errors are clustered at the NAICS6 level.

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

Table A.2: Inverse R&D Labor Supply Elasticity Estimates — Controls

	(1)	(2)	(3)
	R&D Wage Growth		
R&D Employment Growth	0.434***	-0.040	-0.023
	(0.162)	(0.125)	(0.147)
— × Above Median R&D Employment		0.711***	
		(0.186)	
— × Above Median R&D Return			0.676***
			(0.161)
Controls	✓	✓	✓
First stage F stat. (Main)	72	43	38
First stage F stat. (Inter.)	–	31	76
Observations	12,707	12,707	12,707

Note: R&D employment and wage growth are log differences between $t-2$ and $t+3$. Controls include lagged inventor wage and employment growth. R&D employment growth is instrumented for with stock market returns in $t-1$. All regressions control for NAICS3 × year fixed effects. F statistics reported are based on Sanderson and Windmeijer (2015). Standard errors are clustered at the NAICS6 level.

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

Table A.3: Inverse R&D Labor Supply Elasticity Estimates — Alternative Instrument

	(1)	(2)	(3)
	R&D Wage Growth		
R&D Employment Growth	0.571*	0.023	0.225
	(0.337)	(0.218)	(0.351)
— × Above Median R&D Employment		0.953***	
		(0.323)	
— × Above Median R&D Return			0.628***
			(0.202)
Controls			
First stage F stat. (Main)	16	9	8
First stage F stat. (Inter.)	–	11	31
Observations	10,239	10,239	10,239

Note: R&D employment and wage growth are log differences between $t-2$ and $t+3$. R&D employment growth is instrumented for with TFP growth. All regressions control for NAICS3 × year fixed effects. F statistics reported are based on Sanderson and Windmeijer (2015). Standard errors are clustered at the NAICS6 level.

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

Table A.4: Inverse R&D Labor Supply Elasticity Estimates — Productivity

	(1)	(2)	(3)
	R&D Wage Growth		
R&D Employment Growth	0.447***	-0.037	0.010
	(0.145)	(0.126)	(0.160)
— × Above Median R&D Employment		0.756***	
		(0.206)	
— × Above Median R&D Return			0.658***
			(0.197)
Inventor Productivity Growth	0.505***	0.375***	0.445***
	(0.100)	(0.076)	(0.091)
First stage F stat. (Main)	70	41	33
First stage F stat. (Inter.)	–	30	100
Observations	12,518	12,518	12,518

Note: R&D employment and wage growth are log differences between $t-2$ and $t+3$. Inventor productivity is the average patents per year produced from inventors employed by the firm. R&D employment growth is instrumented for with stock market returns in $t-1$. All regressions control for NAICS3 × year fixed effects. F statistics reported are based on Sanderson and Windmeijer (2015). Standard errors are clustered at the NAICS6 level.

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

Table A.5: R&D Returns Correlate with R&D Employment

	(1)	(2)	(3)	(4)	(5)	(6)
			R&D Returns			
R&D Employment	0.295***	0.276***				
	(0.036)	(0.054)				
Employment		0.019				
		(0.031)				
Lagged Excess Returns			0.215***			
			(0.023)			
Lagged TFP Growth				0.219***		
				(0.055)		
Firm R&D Dominance					0.161***	
					(0.039)	
Inventor Specialization						0.178**
						(0.079)
Within R-sq.	0.13	0.13	0.01	0.00	0.02	0.00
Observations	11,062	11,050	9,296	7,587	9,897	11,048

Note: All variables in logs exce[t for excess returns and TFP growth. All regressions control for NAICS3 $\times$ year fixed effects. Standard errors are clustered at the NAICS6 level.

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

Online Appendix

Not for publication

B Online Model Appendix

B.1 Baseline Model

B.1.1 Characterization of Decentralized BGP Equilibrium

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

Household. Household optimization yields the familiar Euler equation:

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

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

The supply of production and research labor satisfies

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

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

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

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

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

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

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

Clearing the production labor market, we have

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

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

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

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

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

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

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

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

$$\ell_{kt} = \left(\frac{\gamma \cdot A_k \cdot \mathcal{V} \cdot \mathbb{E}_t[z_{kt+1}|z_{kt}]}{W_{kt} \cdot (1 + 1/\epsilon_{kt}) \cdot R} \right)^{\frac{1}{1-\gamma}}.$$

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

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

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

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

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

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

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

B.1.2 Characterization of the Planner Equilibrium

Static optimality conditions. Planner output and consumption:

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

Planner production labor supply:

$$L_{P,t} = \alpha_P^{\frac{1}{1+\epsilon}}$$

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

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

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

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

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

We can solve for the marginal value of Q_t as

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

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

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

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

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

B.1.3 Proofs and Additional Results

Proof of Proposition 1. Following the results developed above, the labor supply curve is given by

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

It follows directly, that any shift in R&D employment due to a change in the R&D subsidy rate (or any other shift in the demand for, but not supply of, R&D workers) yields the shift in R&D wages described in the proposition. The remaining observations result directly from the formula. □

Proof of Proposition 2. The result follows directly from the derivations for the decentralized and planner equilibria above. First, one can confirm that with $\bar{\ell} = 0$, the first order conditions are perfectly proportional, i.e., the relative allocation coincides. That also implies that the allocation of R&D workers is efficient if their supply is perfectly inelastic. Second, imposing R&D subsidies that depend on the firm type and perfectly offset the wage elasticity yield the efficient relative and total allocation. As is standard, output subsidies can be used to solve inefficiencies in the production sector. Finally, it is straight-forward to confirm that monopsony power reduces the relative demand for R&D workers among larger firms as long as $\bar{\ell} > 0$. $\square$

Proposition 1 highlights that monopsony power materializes in form of a finite labor supply elasticity in response to firm-specific demand shocks. Proposition 4 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 4. *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*

$$\left.\frac{\partial \ln W_{R,kt}}{\partial \ln \ell_{kt}}\right|_{\Delta \tau_t} = \frac{1}{\epsilon}, \tag{B.2}$$

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.*

Proof of Proposition 4. It is straight-forward to show that starting with an equilibrium, the first order conditions for the firm continue to hold with a constant ℓ_{kt}/L_R when L_R rises with $(1 - \tau)$ such that $\left(L_R^{\frac{1}{\epsilon}} \cdot (1-\tau)\right)^{\frac{1}{1-\gamma}} \cdot L_R^{-1}$ remains constant. Resultingly, the wage elasticity induced by such a shock is $1/\epsilon$. $\square$

Proof of Proposition 3. 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. $\square$

B.2 Quantitative Model

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

B.2.1 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

$$\max_{L_{P,t},\{x_{jt}\}_{j\in\mathcal{Q}_t}} Y_t - W_{P,t}\cdot L_{P,t} - \int_{\mathcal{Q}_t} p_{jt}\cdot x_{jt}dj \quad \text{s.t.} \quad Y_t = L_{P,t}^{1-\alpha}\int_{\mathcal{Q}_t} z_{jt}^{1-\alpha}\cdot x_{jt}^{\alpha}dj, \quad \text{(B.3)}$$

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

$$\frac{W_{P,t}}{C_t} = \frac{Y_t}{C_t}\cdot\frac{1-\alpha}{L_{P,t}} \quad \text{and} \quad p_{jt} = \alpha\cdot\left(\frac{L_{P,t}\cdot z_{jt}}{x_{jt}}\right)^{1-\alpha}. \quad \text{(B.4)}$$

Intermediate good producers. There is a unit mass of firms owning the exclusive production rights to Intermediate goods, which can be produced with constant unit cost ψ in terms of the final good. For each intermediate good, the proprietor solves

$$\max_{x_{jt}} \quad p_{jt}\cdot x_{jt} - \psi\cdot x_{jt} \quad \text{(B.5)}$$

subject to the product demand curve detailed above. Profit maximizing monopoly price p_M is constant across firms and given by $p_M = \frac{\psi}{\alpha}$. All prices are relative to the final good whose price is normalized to 1. I set $\psi = \alpha$ when taking the model to the data.

Equilibrium quantities x_{kt} are given by

$$x_{kt} = z_{kt}\cdot L_{P,t}\cdot\left(\frac{\psi}{\alpha^2}\right)^{-\frac{1}{1-\alpha}} \quad \text{(B.6)}$$

Equilibrium profits are given by

$$\pi_{kt} = \tilde{\pi}_t \cdot z_{kt} \quad \text{with} \quad \tilde{\pi}_t = (1-\alpha) \cdot \alpha^{\frac{1}{1-\alpha}} \cdot \left(\frac{\psi}{\alpha}\right)^{-\frac{\alpha}{1-\alpha}} \cdot L_{P,t}. \tag{B.7}$$

I denote the mass of available intermediate goods by Q_t and their average quality level as $z_t = \frac{1}{Q_t}\int_0^1 \int_{Q_{kt}} z_{kt} \cdot dz \cdot dk$, where Q_{kt} is the mass of intermediate goods owned by firm k. 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, $\mathcal{R}_{kt}$. Market clearing thus requires

$$Y_t = C_t + \int_{\mathcal{Q}_t} \psi \cdot x_{jt} \cdot dj + \int_0^1 \mathcal{R}_{kt} \cdot dk. \tag{B.8}$$

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

$$Y_t - I_t = Q_t \cdot z_t \cdot L_{P,t} \cdot (1-\alpha^2) \cdot \alpha^{\frac{\alpha}{1-\alpha}} \cdot \left(\frac{\alpha}{\psi}\right)^{\frac{\alpha}{1-\alpha}}. \tag{B.9}$$

Workers and Labor Markets. A representative household owns all firms and supply labor in form of production workers $L_{P,t}$ and researchers $\{\ell_{kt}\}_{k\in[0,1]}$. Wage income from production workers, $W_{P,t}$, and researchers, $W_{R,kt}$, bond holdings $R_t \cdot B_t$, and firm ownership Π_t are either 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

$$\begin{aligned}
\max \quad & \sum_{t=0}^{\infty} \beta^t \left(\log C_t - \frac{\epsilon}{1+\epsilon} \left(\alpha_P \left(\frac{L_{P,t}}{\alpha_P}\right)^{\frac{1+\epsilon}{\epsilon}} + \alpha_R \left(\frac{L_{R,t}}{\alpha_R}\right)^{\frac{1+\epsilon}{\epsilon}} \right) \right) \\
\text{s.t.} \quad & L_{R,t} = \left(\underline{\ell} + \frac{1}{1+\xi}\right)^{-1} \cdot \left(\int_0^1 \ell_{kt} \cdot \left(\underline{\ell} + \frac{1}{1+\xi} \left(\frac{\ell_{kt}}{L_{R,t}}\right)^{\xi} \right) dk \right) \\
& B_{t+1} + C_t = R_t \cdot B_t + W_{P,t} \cdot L_{P,t} + \int_0^1 W_{R,kt} \cdot \ell_{kt} dk + \Pi_t
\end{aligned} \tag{B.10}$$

Household optimization yields standard Euler equation:

$$\frac{C_{t+1}}{C_t} = \beta \cdot R_{t+1}. \tag{B.11}$$

Supply of production labor satisfies

$$\frac{W_{P,t}}{C_t} = \left(\frac{L_{P,t}}{\alpha_P}\right)^{\frac{1}{\epsilon}}. \tag{B.12}$$

Supply for research labor satisfies

$$\frac{W_{R,kt}}{C_t} = \left(\frac{L_{R,t}}{\alpha_R}\right)^{\frac{1}{\epsilon}} \cdot \left(\underline{\ell} + \frac{1}{1+\xi} + \frac{\xi}{1+\xi} \cdot \int_0^1 \left(\frac{\ell_{kt}}{L_{R,t}}\right)^{1+\xi} dk\right)^{-1} \cdot \left(\underline{\ell} + \left(\frac{\ell_{kt}}{L_{R,t}}\right)^{\xi}\right) \tag{B.13}$$

Innovation. Intermediate goods firms employ 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

$$M_{kt+1} = Q_t \cdot A_k \cdot \left(\alpha_L^{\frac{1}{\nu}} \left(\ell_{kt}\right)^{\frac{\nu-1}{\nu}} + (1-\alpha_L)^{\frac{1}{\nu}} \left(\frac{R_{kt}}{Q_t}\right)^{\frac{\nu-1}{\nu}}\right)^{\frac{\nu}{\nu-1}\cdot\gamma}. \tag{B.14}$$

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.

The quality-adjusted stock of blueprints $\mathcal{Q}_{kt}$ evolves according to

$$\mathcal{Q}_{kt+1} = M_{kt+1} \cdot z_{kt+1} + \mathcal{Q}_{kt}^{N}. \tag{B.15}$$

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.[21] It follows a persistent, stochastic process:

$$\ln z_{kt+1} = (1-\rho) \cdot \mu + \rho \cdot \ln z_{kt} + \sigma \cdot \nu_{kt+1} \quad \text{with} \quad \nu_{kt+1} \overset{i.i.d.}{\sim} N(0,1). \tag{B.16}$$

[21] Alternatively, one could assume that firm-level demand for all products fluctuates concurrently. Such an assumption will affect the precise algebra of the model, but not its qualitative or quantitative properties.

The firms' optimization problem is thus given by

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

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

$$
V_t^Q = \tilde{\pi}_t + \frac{1}{R_{t+1}} \cdot V_{t+1}^Q \qquad \textit{with} \quad \tilde{\pi}_t \equiv (1-\alpha) \cdot \alpha^{\frac{1}{1-\alpha}} \cdot \left(\frac{\psi}{\alpha} \right)^{-\frac{\alpha}{1-\alpha}} \cdot L_{P,t} \tag{B.17}
$$

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

$$
\begin{aligned}
V_t(z_{kt}, A_k) = \max_{\ell_{kt}, \mathcal{R}_{kt}} \Big\{ & - W_{kt} \cdot \ell_{kt} - \mathcal{R}_{kt} \\
& + \frac{1}{R_{t+1}} \mathbb{E}_t \left[M_{kt+1} \cdot z_{kt+1} \cdot V_{t+1}^Q + V_{t+1}(z_{kt+1}, A_k) \big| z_{kt} \right] \Big\}.
\end{aligned} \tag{B.18}
$$

The firm's innovation choice problem is thus given by

$$
\max_{\ell_{kt}, \mathcal{R}_{kt}} \quad R_{t+1}^{-1} \cdot \mathbb{E}_t[z_{kt+1} | z_{kt}] \cdot M_{kt+1} \cdot V_{t+1}^Q - W_{R,kt} \cdot \ell_{kt} - \mathcal{R}_{kt} \quad \text{s.t.} \quad \text{(B.13) and (B.14)}.
$$

The aggregate state of technology evolves according to

$$
\mathcal{Q}_{t+1} = \mathcal{Q}_t + \int_0^1 M_{kt+1} \cdot z_{kt+1} \cdot dk. \tag{B.19}
$$

B.2.2 Simulation and Quantification

I calibrate the model through moment matching as discussed in the main text. For a given set of parameters I first solve the model along the balance growth path and then simulate a listed firms for 100,000 periods.I construct all moments exactly as in the data and run the same regressions. To account for potential biases due to share-based compensation, I follow the third example in Appendix Section B.3 to construct a set of wages adjusting for stock-based compensation. Using these wages, I then calculate R&D expenditure per worker as I do in the data. I present calibrations and counterfactuals for alternative models of stock-based compensation in Online Appendix B.8. I then calculate a weighted distance of target and model moments, which I minimize using standard solvers.

Using the calibrated model, I construct counterfactuals in which monoposony power is overcome through targeted subsidies. In my baseline, I consider the case where subsidies are financed through lumpsum taxation. Naturally, such a scheme will not only yield a more efficient allocation of researchers across firms, but will also improve the aggregate incentives for R&D and, thus, yield an expansion of aggregate R&D employment. To disentangle the relative and absolute effects, I consider two additional counterfactuals. In the first, I fix the number of researchers employed $\tilde{L}_R = \int_0^1 \ell_{kt} \cdot dk$ through a general taxation of research activity. In the second, I instead do not implement any size-dependent R&D policy and only implement the change in $\tilde{L}_R$ between the baseline monopsony and no monopsony cases through a general subsidy of research activity.

B.3 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 stock market 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

$$W_{kt} = W_{C,kt} + s_{kt} \cdot V_{kt}, \tag{B.20}$$

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 stock market 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. 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

$$s = \frac{\mathbb{E}_{t-1}[s_{kt} \cdot V_{kt}]}{\mathbb{E}_{t-1}[s_{kt} \cdot V_{kt}] + \mathbb{E}_{t-1}[W_{C,kt}]}. \tag{B.21}$$

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.

B.4 Extensions

B.4.1 The Cost of Monopsony under Free Entry

This Appendix discusses the quantitative implication of monopsony model when the number of firms is determined by a free entry condition. I briefly discuss how I introduce free entry into the model and how I construct counterfactuals before presenting the associated estimates for the cost of monopsony power.

Model. I introduce entry by allowing for the posibility that the mass of firms, which I denote by $\mathcal{M}_t$, is determined by a free entry condition stating that the expected value of a firm without existing patents has to be equal to entry costs, which I model as $Q_t \cdot \phi_E \cdot \mathcal{M}_t^{\varphi_E}$. Resultingly, the free entry condition is given by

$$\mathbb{E}[V_{it}/Q_t] = \phi_E \cdot \mathcal{M}_t^{\varphi_E}.$$

Larger values of φ_E make M_t less responsive—indeed $\varphi_E \to \infty$ yields the case of a fixed mass of firms in the limit. To preserve comparability with the model, which assumes a fixed mass of firms $\mathcal{M}_t = 1$, I assume that entry costs are paid in the past rather than affecting resource constraints moving forward. Note also that the equilibrium number of firms is constant along the BGP.

I parametrize ϕ_E to ensure that $M_t = 1$ in baseline. I then consider two counterfactuals. In the first counterfactual, I assume that the planner implements a targeted subsidy scheme that perfectly offsets firms' disincentive to hiring due to monopsony power. As discussed below, this intervention entails a substantial subsidy on average, which raises firm values and, thus, the incentives to enter. I, thus, consider a second counterfactual in which I implement a non-targeted tax on R&D expenditure that fully finances the subsidy scheme. In both scenarios I set $\varphi_E = 0$ to explore the full "free-entry" case without crowding out, which could be understood as the other extreme compared the the $\varphi_E \to \infty$ that implicitly underpins the baseline.

Counterfactuals. Column (7) of Table B.3 reports the aggregate results for the counterfactuals with the baseline counterfactual reported in column (2) for reference. Free entry increases the welfare costs of monopsony power significantly. This effect is driven by an expansion of the active firms and R&D employment in both cases. Both are less pronouced in the scenario with budget neutral taxation and subsidies. The welfare gains from combating monopsony power increase by about factor 5 in the first scenario and turn decidedly positive in the second one. The intuition for the latter is that entry pushes down the average number of R&D workers per firm, which lowers wage elasticities, especially for larger firms that require high subsidies. Resultingly, the required general tax on R&D to recover the subsidy payments are lower, which reduces their drag on total R&D employment.

B.4.2 Monopsony and Price Discrimination

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.

Background. We can write the labor disutility for R&D workers equivalently as

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

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

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

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:

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

Resultingly, firms' marginal costs are the true marginal costs of hiring the last worker and planner and decentralized equilibrium agree on the relative marginal cost of R&D workers across firms. 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:

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

This phenomenon occurs as rising wages at the margin also push up the average wage, even though inframarginal wages are unaffected.

Model. In practice, firms' power to discriminate is likely limited due to information asymmetries and/or fairness considerations. I, thus, consider a model in which workers are paid a fraction α_D of the fully discriminatory wage and a fraction $1-\alpha_D$ of the required marginal wage given total hiring. Total labor cost are then satisfy

$$C(\ell_{kt}) \propto \ell_{kt} \cdot \left(\bar{\ell} + \frac{1+(1-\alpha_D)\cdot\xi}{1+\xi} \cdot \left(\frac{\ell_{kt}}{L_{R,t}}\right)^{\xi}\right) \tag{B.22}$$

Resultingly, marginal cost become proportional to

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

Evidently, marginal costs are proportional to marginal disutility for $\alpha_D = 1$ and to marginal average disutility for $\alpha_D = 0$.[22]

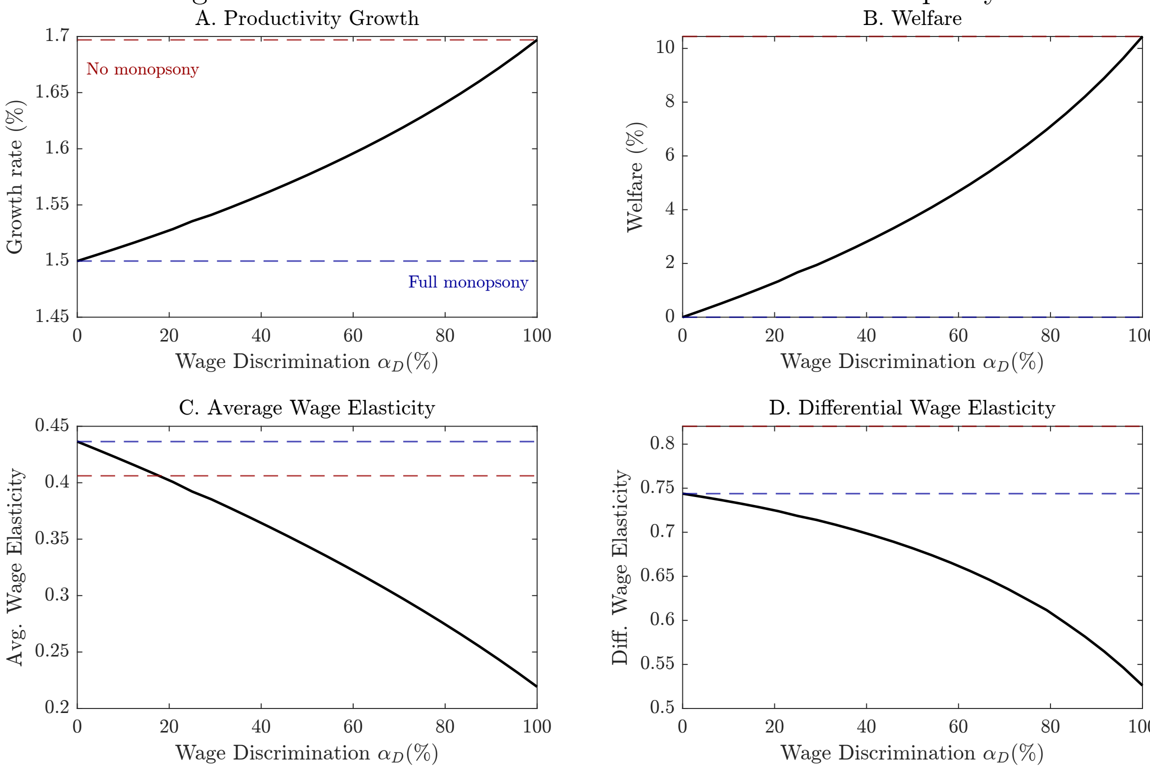
Increasing Wage Discrimination. Figure B.2 explores the impact of price discrimination quantitatively in the main calibration. For reference, I also report values for the baseline monopsony case and the case of no monopsony implemented through subsidies. As shown in Panels A and B, Growth and welfare converge to the no monopsony case as the model approaches full price discrimination. however, the gap remains large at intermediate values.

Calibration and Counterfactuals for $\alpha_D = 0.5$. Panels C and D in Figure B.2 highlight that the estimated wage elasticities fall significantly as we assume higher levels of price discrimination. To account for this fact, I re-calibrate the model via moment matching assuming as intermediate level of price discrimination, $\alpha_D = 0.5$, and report the associated parameters in column (6) of Table B.2. The counterfactuals, presented in column (6) of Table B.3, suggest that monopsony power continues to be

[22] The elasticity of the average wage with respect to labor is

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

Figure B.2: Price Discrimination and the Cost of Monopsony



Notes: The figure shows the impact of increasing firms' ability to price discriminate among workers. All models employ the main calibration and then impose alternative values for α_D. The dotted red and blue lines show the outcomes under the calibrated model and the counterfactual with no monopsony power respectively.

a significant drag on economic growth and welfare.

B.5 Regression bias due to materials

The relative demand for R&D inputs is given by

$$\frac{r_{kt}}{\ell_{kt}} = \left(\frac{1-\alpha_L}{\alpha_L}\right) \cdot ((1+\epsilon_{kt}) \cdot w_{kt})^{\sigma} \tag{B.23}$$

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

$$\ell_{kt} = \alpha_L \cdot \underbrace{\left(\frac{w_{it} \cdot (1+\epsilon_{it})}{P_{R,t}}\right)^{-\sigma}}_{\textit{relative demand effect}} \cdot \underbrace{\left(\frac{\gamma \cdot A_k \cdot \mathbb{E}[z_{kt+1}|z_{kt}]}{P_{R,t}}\right)^{\frac{1}{1-\gamma}}}_{\textit{total demand effect}} \tag{B.24}$$

Denoting R&D expenditure per work by $\tilde{w}_{kt} = (w_{kt} \cdot l_{kt} + r_{kt})/\ell_{kt}$, one can show that

$$\frac{\partial \ln \tilde{w}_{kt}}{\partial \ln \ell_{kt}} = \frac{\partial \ln w_{kt}}{\partial \ln \ell_{kt}} + \underbrace{\frac{r_{kt}}{l_{kt} \cdot w_{kt} + r_{kt}} \cdot \frac{\partial \ln \left((1+\epsilon_{kt})^{\sigma} \cdot w_{kt}^{\sigma-1}\right)}{\partial \ln \ell_{kt}}}_{=bias} \tag{B.25}$$

Thus, any estimate of the wage elasticities using R&D per worker is necessarily biased. However, the direction and extent is ex-ante unclear and depends on the elasticity of substitution between materials and workers. Note also 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.

B.6 Bias in Calibration

This section highlights the importance of accounting for stock-based compensation and intermediate inputs. Table B.1 reports the regression coefficients when estimating columns (1) and (2) in 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 B.1: Wage Regression in Data and Model

Model	Reg. (1)	Regression (2)	
	Main	Base	Inter.
Data	0.437	0.000	0.746
Baseline	0.437	0.197	0.746
+ *Stock-based compensation*	*0.438*	*0.198*	*0.750*
+ *Intermediate inputs*	*0.425*	*0.197*	*0.720*
+ *Both*	*0.426*	*0.198*	*0.723*
Adjusted	0.436	0.201	0.747

Notes: This table reports coefficient estimates for the main specifications from the data and simulated model data. Column (1) reports estimates for specification (18). Columns (2) and (3) report coefficient estimates from specification (19). The baseline model has neither stock-based compensation nor material inputs in R&D. Rows 3 and 4 add these to the simple calibration, respectively, without recalibrating other parameters, while row 5 adds both simultaneously. The final row re-calibrates the model with both extensions.

B.7 Regression Bias with Supply Shocks

A classic problem when estimating labor supply elasticities are labor supply shocks (Manning, 2003). Consider an extension of my framework with labor supply shocks in the form of labor disutility shifters α_{it} and for simplicity assume $\bar{\ell} = 0$. Labor supply is given by

$$L_{Rt} = \int_0^1 \alpha_{kt}^{-1} \cdot \ell_{it} \cdot \left(\frac{\ell_{kt} \cdot \alpha_{kt}^{-1}}{L_R} \right)^{\xi} \cdot dk$$

First order conditions for labor supply confirm that larger values of α_{kt} imply lower disutility of working for the specific firm:

$$\frac{W_{kt}}{C_t} = (1+\xi) \cdot \left(\frac{L_{Rt}}{\alpha_R} \right)^{\frac{1}{\epsilon}} \alpha_{kt}^{-1} \left(\frac{\ell_{kt} \cdot \alpha_{kt}^{-1}}{L_{Rt}} \right)^{\xi}$$

Focusing on the case with only in R&D, labor demand for the firm satisfies

$$\gamma \cdot \theta_{kt} \cdot \ell_{kt}^{\gamma-1} = (1+\xi) \cdot W_{kt}.$$

As a result, equilibrium quantities and wages satisfy

$$\ell_{kt} \propto \theta_{kt}^{\frac{1}{\xi+1-\gamma}} \cdot \alpha_{kt}^{\frac{1+\xi}{\xi+1-\gamma}} \quad \text{and} \quad W_{kt} \propto \theta_{kt}^{\frac{\xi}{\xi+1-\gamma}} \cdot \alpha_{kt}^{\frac{(1+\xi)(1-\gamma)}{\xi+1-\gamma}}$$

It follows that estimating the labor supply elasticity with OLS under a combination of demand and supply shocks would yield an estimate with a downwards bias that is increasing in the relative prominence of supply (α_{kt}) shocks:

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

Whether such a bias would also affect differential estimates is ex-ante unclear. The formula above suggests that the bias is uniform across firms if the nature of monopsony power is also uniform.

B.8 Calibration and Counterfactuals for Alternative Models

Table B.2: Alternative Calibrations

A. Parameters		(1)	(2)	(3)	(4)	(5)	(6)
Parameter	Symbol	Simple	Main	$\theta =$ 1.5	Bonus II	Bonus IV	$\alpha_D =$ 0.5
A.1. External calibration							
Discount factor	β	0.96	0.96	0.96	0.96	0.96	0.96
Labor supply elasticity	ϵ	0.50	0.50	0.50	0.50	0.50	0.50
R&D scale elasticity	γ	0.50	0.50	0.50	0.50	0.50	0.50
Share of non-listed firms	ζ	0.05	0.05	0.05	0.05	0.05	0.05
Markup parameter	α	0.80	0.80	0.80	0.80	0.80	0.80
Elas. of substitution in R&D	θ	0.50	0.50	1.50	0.50	0.50	0.50
A.2. Internal calibration							
Labor disutility production	α_P	0.205	0.205	0.205	0.205	0.205	0.205
Labor disutility R&D	α_R	0.097	0.121	0.089	0.118	0.281	0.123
Labor weight in R&D	α_L	1.000	0.968	0.594	0.968	0.969	0.968
R&D productivity listed	A_l	0.262	0.261	0.331	0.263	0.220	0.263
R&D productivity unlisted	A_{nl}	0.013	0.014	0.024	0.014	0.013	0.014
Std. dev. R&D prod. shocks	σ	0.266	0.238	0.226	0.241	0.218	0.241
Autocorr. R&D prod. shocks	ρ	0.979	0.985	0.979	0.984	0.994	0.984
Avg. R&D supply elasticity	$\bar{\xi}$	2.008	1.922	1.908	1.963	1.366	1.963
Rel. R&D supply elasticity	ℓ	106.7	57.3	153.8	68.3	2.6	38.0
B. Moments		(1)	(2)	(3)	(4)	(5)	(6)
Moment	Data	Simple	Main	$\theta =$ 1.5	Bonus II	Bonus IV	$\alpha_D =$ 0.5
Growth rate	0.015	0.015	0.015	0.015	0.015	0.015	0.015
Relative R&D listed vs non-listed	35	35	35	35	35	35	35
Std. dev. of R&D growth-rate	0.316	0.316	0.316	0.316	0.316	0.316	0.316
Autocorr. of R&D	0.922	0.968	0.923	0.904	0.922	1.092	0.924
Wage elasticity	0.437	0.437	0.436	0.437	0.437	0.434	0.435
Wage elas. for small R&D	0	0.197	0.201	0.184	0.205	0.198	0.202
Δ wage elas. large R&D	0.746	0.746	0.747	0.746	0.746	0.746	0.746
Labor share in R&D	0.79	1	0.79	0.79	0.79	0.79	0.79
R&D employment	0.047	0.047	0.047	0.047	0.047	0.047	0.047
Production employment	0.286	0.286	0.286	0.286	0.286	0.286	0.286

Notes: This table reports calibrated parameter values and targeted moments in the data and model for alternative model specifications. Panel A reports parameter values distinguishing between externally calibrated parameters in Panel A.1 and internally calibrated parameters in Panel A.2. Panel B reports the targeted moments from the data and the model values from the calibration. In the simple model, R&D is produced only with labor and there is no stock-based compensation. In Bonus II, stock-based compensation is determined based on expected wages in the next period rather than current wages. In Bonus IV, workers receive a bonus whenever the firm earns positive stock returns. The final column reports results for a model with partial price discrimination among workers. See text for additional details.

Table B.3: Counterfactuals for Alternative Calibrations

Outcome	(1) Simple	(2) Main	(3) $\theta = 1.5$	(4) Bonus II	(5) Bonus IV	(6) $\alpha_D = 0.5$	(7) Entry
A. Lump-sum Taxation							
Δ Growth Rate	0.21 p.p.	0.20 p.p.	0.14 p.p.	0.20 p.p.	0.19 p.p.	0.12 p.p.	0.48 p.p.
Δ Welfare	10.5%	10.6%	7.1%	10.4%	12.3%	6.3%	19.8%
Δ R&D Employment	1.7%	1.9%	2.7%	2.0%	7.0%	0.4%	8.4%
Δ Firm Value	15.6%	13.6%	14.3%	13.8%	9.0%	10.2%	-0.0%
Avg. R&D Subsidy	48.8%	44.0%	35.3%	44.0%	44.9%	45.3%	43.2%
Δ Firms	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	21.8%
B. Budget-neutral R&D Taxation and Subsidies							
Δ Growth Rate	0.00 p.p.	-0.01 p.p.	-0.04 p.p.	-0.01 p.p.	-0.03 p.p.	-0.09 p.p.	0.20 p.p.
Δ Welfare	6.0%	6.7%	2.7%	6.6%	8.8%	2.7%	13.5%
Δ R&D Employment	-21.1%	-20.4%	-13.2%	-20.3%	-17.7%	-22.4%	-15.5%
Δ Firm Value	8.9%	10.4%	11.9%	10.6%	5.6%	6.7%	-0.0%
Avg. R&D Subsidy	0.0%	-0.0%	0.0%	0.0%	0.0%	0.0%	-0.0%
Δ Firms	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	18.1%

Notes: This table reports counterfactuals for offsetting monopsony power through targeted subsidies. Each column reports the change in key outcomes for a different calibration. In the simple model, R&D is produced only with labor and there is no stock-based compensation. In $\theta = 1.5$, I assume that labor and material are substitutes instead of complements in R&D. In Bonus II, stock-based compensation is determined based on expected wages in the next period rather than current wages. In Bonus IV, workers receive a bonus whenever the firm earns positive stock returns. The sixth column reports results for a model with partial price discrimination among workers. The last column reports counterfactuals for a model with free entry. See text and appendix for additional details.

Table B.4: Key Moments for Alternative Parameterizations

Scenario	Wage elasticity	Wage elas. for large firms	Δ Growth	Δ R&D Empl.	Δ Welfare
Baseline calibration	0.436	0.747	0.20 p.p.	1.9%	10.6%
Lower variance of R&D shocks σ	0.633	0.623	0.20 p.p.	3.0%	7.7%
Higher variance of R&D shocks σ	0.313	0.736	0.20 p.p.	1.5%	13.2%
Lower persistence of R&D shocks ρ	0.533	0.684	0.20 p.p.	2.4%	9.0%
Higher persistence of R&D shocks ρ	0.306	0.784	0.20 p.p.	1.5%	13.0%
Lower relative productivity of unlisted firms A_{nl}/A_l	0.491	0.768	0.21 p.p.	1.8%	11.1%
Higher relative productivity of unlisted firms A_{nl}/A_l	0.390	0.720	0.18 p.p.	2.4%	10.3%
Lower avg. R&D supply elasticity ξ	0.235	0.429	0.14 p.p.	1.9%	9.9%
Higher avg. R&D supply elasticity ξ	0.685	1.031	0.24 p.p.	3.8%	11.4%
Lower rel. R&D supply elasticity $\bar{\ell}$	0.541	0.782	0.21 p.p.	2.3%	10.6%
Higher rel. R&D supply elasticity $\bar{\ell}$	0.366	0.703	0.19 p.p.	1.8%	10.7%
Lower R&D supply disutility α_R	0.436	0.747	0.20 p.p.	1.9%	10.6%
Higher R&D supply disutility α_R	0.436	0.747	0.20 p.p.	1.9%	10.6%
Lower labor intensity in R&D α_L	0.430	0.737	0.20 p.p.	2.0%	10.5%
Higher labor intensity in R&D α_L	0.442	0.757	0.20 p.p.	1.8%	10.7%

Notes: This table reports selected moments and statistics for alternative parameterizations as a sensitivity check. Each row reports alternative values for calibrations changing the indicated parameter by +/- 25% of its value in the main calibration, except for the autocorrelation, where parameterizations +/- 0.005 of the main calibration are reported, and labor intensity of R&D, where parameterizations +/- 0.01 of the main calibration are reported. See text and appendix for additional details.

C Online Empirical Appendix

C.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. 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 C.1.

As reported in Table C.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% (Autor et al., 2020). Hence, R&D is a very labor intensive task, justifying the focus on labor markets in R&D.

Table C.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.