Labor market power and innovation

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Abstract:

This paper examines how labor market power shapes how firms innovate and grow. We develop an endogenous growth model where firms optimize R&D spending to increase their future productivity while facing an upward-sloping labor supply curve, generating monopsony power. This creates two opposing distortions: (1) monopsonistic firms have stronger incentives to innovate and grow as they enjoy larger profits, but (2) firm growth increases (infra-)marginal labor costs by pushing firms up the labor supply curve, which reduces the returns to productivity-enhancing innovation. Theoretically, the first effect dominates for small firms, while the second is stronger for large firms. We test these predictions using rich firm-level data from the German manufacturing sector (1995–2018) to estimate firms' productivity and labor market power. Empirically, we find that, conditional on size, labor market power negatively correlates with R&D investment. Furthermore, small (large) firms in high-monopsony-power regions exhibit relatively high (low) R&D spending, compared to competitive labor markets, which aligns with our model's predictions. When applying our model to the data, we find that East Germany's higher labor market power can explain 24.7% of the persistent productivity gap between East and West Germany and depresses overall GDP growth by 0.2% p.a.

Keywords: Innovation, Labor Market Power, Productivity, Growth
JEL: D24, O31, O40, J42, L10, L60

1 Introduction

Throughout the developed world, firms' labor market power (LMP) is rising, especially after 2000: Firms' markdown increased from 1.1 to 1.6 in the US (Kirov and Traina, 2023; Yeh et al., 2022) and from 1.34 to 1.42 in German manufacturing (Mertens, 2022). Research has also documented substantial welfare losses from LMP (Berger et al., 2022; Bachmann et al., 2022). Consequently, understanding the effects of LMP has become much more important.

Our paper estimates firm labor market power and shows that its regional prevalence is associated with low innovation and productivity. We propose that this is due to LMP negatively impacting firms' incentives to grow as they face monopsonistic labor markets with upward-sloping labor supply curves. These labor supply curves imply that firms have to increase wages as they grow, which partially offsets the returns to innovation. To assess the quantitative importance of this mechanism, we build a rich endogenous growth model with incumbent innovation as well as monopsonistic regional labor markets and entry. Reproducing our empirical findings in the model, LMP distorts incumbents' static employment decisions and their dynamic R&D decisions. It also distorts entry towards high-LMP labor markets. Calibrating the model to firm-level data from Germany allows us to quantify the effects of LMP via counterfactual simulations. We conclude that LMP has depressed German productivity growth by 0.2% p.a. since 1995. Furthermore, through all our mechanisms, labor market power can account for 24.7% of the well-documented persistent productivity gap between East and West Germany.

In our endogenous growth model, firms invest in innovation to increase their productivity and size, entrepreneurs try to enter the economy and knowledge diffuses. All of these decisions at the micro level drive the evolution of aggregate productivity. The key novelty of our model is that firms do not face a perfectly elastic labor supply, but instead an upward-sloping labor supply curve that differs across regions. This generates LMP in our model and gives rise to two important opposing effects: On the one hand, firms enjoy higher profits after becoming large due to their monopsony power. On the other hand, moving up the labor supply curve increases the marginal and infra-marginal cost of labor. Our model allows us to study how these two opposing effects shape firms' decision to grow through innovation. It turns out that at a small firm size the former effect dominates: Small firms in monopsonistic labor markets have a stronger incentive to grow relative to competitive labor market firms, as this allows them to better exploit their monopsony power. However, once firms are sufficiently large, the latter effect of increasing infra-marginal labor costs dominates and they are discouraged from innovation and growth.

As a result, the model predicts and helps explain two empirical relationships that we find in firm-level data: Firstly, in monopsonistic labor markets, small firms have comparatively high R&D expenditures given their size. Vice versa, large firms' R&D expenditures are generally higher, but are relatively smaller in monopsonistic labor markets. Secondly and relatedly, the marginal profit gain from increasing productivity is relatively high for small firms with high monopsony power and relatively low for large firms with high monopsony power. Our theory predicts these patterns and we validate them in the data to provide support for the mechanisms that we propose.

For the calibration of our model and for establishing several empirical facts that inform the model, we utilize German manufacturing firm-level data (1995-2018), which is ideally suited to our analysis. In particular, the data contains information on firms' R&D expenditures which is key for our analysis. To measure labor market power at the firm level, we employ state-of-the-art estimators for total factor productivity (TFP) and labor market power in our German manufacturing firm-level data, following Mertens (2022). This methodology builds on firm-level production function estimation and measures the difference between the marginal revenue productivity of labor and the wage, which would be equal in the absence of labor market distortions. The German micro data contains firm-specific output prices and quantities, which allows us to address the "price-bias" when estimating production functions (De Loecker et al. (2016), Bond et al. (2021)).[1]

Beyond data quality and availability, Germany also offers a unique setting for studying the effects of labor market power on innovation and productivity. The former German separation has resulted in a persistent economic division, where wages and GDP per capita in the formerly socialist East are approximately 20% below the West German levels, even more than 30 years after the German reunification. We find similar and equally persistent differences in labor market power with a considerably higher average level in the East. This regional heterogeneity and data richness make Germany ideal for our micro-data analysis and our findings can contribute to the discussion involving GDP and productivity differences within Germany, which we use as an illustrative case for our quantification.

The empirical analysis of our micro-data shows that generally labor market power is strongly negatively associated with R&D expenditures, and this relationship grows stronger for larger firms. Moreover, while firms with high labor market power can generate much higher profits from increasing productivity at low productivity levels, they have a flatter profit profile with respect to productivity, i.e., their profits rise less if their productivity increases. As a result, the marginal gains from increasing productivity quickly decline for high-labor market power firms as they increase their productivity. These findings help us explain why regions remain structurally weak, such as East Germany, if labor market power is high because it results in lower aggregate productivity, smaller firms and lower innovation.

However, we show that our mechanism is not specific to the German context. Using comparable cross-country data on productivity, labor market power, and R&D investment for several European countries, we demonstrate (i) that regions in other countries also exhibit vast differences in productivity and that they are inversely related to regional levels of labor market power (as in the German case). Furthermore, we show (ii) that R&D investment is negatively

[1] The estimation of labor market power using this approach has been first proposed by De Loecker and Warzynski (2012) and Dobbelaere and Mairesse (2013) and subsequently popularized in a large body of work (Dobbelaere and Kiyota, 2018; Mertens, 2020; Mertens and Mueller, 2022; Mertens, 2021; Caselli et al., 2021; Yeh et al., 2022; Casacuberta and Gandelman, 2023; Rubens, 2023; Biondi et al., 2024; Dobbelaere et al., 2024; Mertens and Schoefer, 2024; Delabastita and Rubens, 2025).

related to labor market power across European regions. These findings are consistent with the mechanisms that we highlight in the German context, suggesting that labor market power has an important role in shaping regional productivity and income differences across Europe.

To illustrate the importance of these empirical findings and our mechanism, we calibrate our model to the German case with its differences in LMP across regions and the initial productivity distributions as observed in 1995. This allows us to simulate the German economy with regional labor market power differences. It also allows us to shut down the LMP channel to quantify its importance: We show that it can explain 24.7% of the persistent productivity gap between East and West Germany in 2020.

The remainder of the paper is organized as follows: Section 2 relates our study to the existing literature. Section 3 describes our firm-level data, explains how we empirically measure labor market power and productivity, and establishes a series of stylized empirical facts. Section 4 derives our theoretical framework that describes the connection between labor market power, productivity, and R&D investment and estimates the value of innovation for different firms and their optimal strategies. Section 5 combines our model with our micro data to conduct a quantitative analysis. Section 6 discusses the relevance of our analysis beyond the German context. Section 7 concludes.

2 Literature Overview

Due to the rise of labor market power, its effects have received renewed attention, and we are not the only ones to study the effect of LMP on aggregate productivity. Bachmann et al. (2022) conclude that the static disincentive to hire workers can explain 40% of the persistent productivity difference between West and East Germany. Mottironi (2024) focuses on the effect of LMP on entry and argues that 40% of the productivity between North and South Italy can be explained by the Southern high LMP leading to the entry of less productive entrepreneurs and thus firms. Both of these papers use comparatively stylized models that do not capture all potential factors in play (in fact, they each capture different ones). Closest to our approach, Armangué-Jubert et al. (2024) also build an endogenous growth model with entry and R&D margins, but their model has no regional dimension. They again argue that roughly 40% of the gap between rich and poor countries can be explained by LMP. In contrast, we build a full model that captures all the effects discussed in the literature and explicitly features multiple regions with different labor market power in the same economy. A strength of this approach is that we can match our model closely to micro data within and across regions to discipline the estimate and also estimate all channels jointly. Since the different papers in the literature argue for huge effects of their specific channels, it is all the more important to consider all channels jointly, which is a main advantage of our paper.

More broadly, our results also add to the literature on non-convergence between countries, but are more pertinent on convergence within countries and especially East and West Germany (see Johnson and Papageorgiou (2020); Uhlig (2006) for surveys). Other researchers also propose labor market power as an important cause for the non-convergence. Bachmann et al.

(2022) develop a similar argument but focus on how the labor supply elasticity affects firms' business models. In their paper, firms remain small if they face a steep labor supply curve to economize on low wages. Our paper, however, focuses on how LMP shapes the incentives of firms to invest into R&D and therefore their long-term growth perspectives. Moreover, we actually estimate labor market power and its effect on innovation in a microeconometric setting, which informs our modelling approach. We also provide evidence that the dampening effect of labor market power on innovation is not an exclusively East German phenomenon. In a planned extension of this paper, we also aim to show that the nature of our innovation mechanism leads to differences in firm dynamics across East and West Germany that exacerbate the lack of productivity convergence in Germany.

We follow the literature on production function and markup estimation, specifically Mertens (2022). We also make use of the literature on estimating the effect of innovation on the firm level, going back to Griliches (1979). We follow Peters et al. (2017); Aw et al. (2011); Doraszelski and Jaumandreu (2013) in combining production function estimation with an intertemporal value function optimization to understand both the effects of innovation and the firms' R&D decision. We are the first to use either of these techniques to study the effect of market power on firms' innovation decisions.

In estimating the detrimental effects of firms' market power, we connect to a large literature documenting and discussing the increase in firms' market power using production function estimation techniques (De Loecker et al., 2020). However, this literature focuses on *product* market power, while we study the effects of rising *labor* market power. The effect of product market power on innovation is ambiguous because some product market power is necessary to incentivize firms to innovate (Aghion et al., 2005, 2006). At the same time, incumbents who already enjoy high markups due to past innovation generally have a lower incentive for innovation (cf. Akcigit and Kerr (2018)). To our knowledge, we are the first to analyze the dynamic innovation incentives of firms with labor market power.

Kline et al. (2019) show that increased rents from successful innovation are not shared equally with all workers. This implies that labor market power over some worker types can increase after innovation. But this is hardly an incentive to innovate by itself as it is a side-effect of the original mechanism and contingent on gaining additional rents through product market power with the newly acquired innovation. We instead study the fundamental first-order effect of labor market power on innovation, abstaining from the product market side. This means that we consider mainly the effects of firms' innovation from the viewpoint of cost-minimization. Our estimation methods however are very flexible and incorporate product market power into the analysis, to also allow for the fact that firms can have both kinds of market power.

Conceptually close to our analysis is a historical study by Rubens (2022). He considers the adoption of specific labor-augmenting or -replacing technologies depending on firms' labor market power over unskilled and skilled workers. He finds that indeed labor market power over unskilled workers makes firms more likely to invest in labor-intensive technologies instead of labor-saving. We add to this finding on static technology adoption by considering innovation, i.e. the firms' dynamic decision whether to push the technology frontier itself.

To estimate these results, we use a large administrative data set of the German manufacturing sector covering all firms with more than 20 employees (AFiD). This data is especially well suited for such an analysis, containing both R&D, wage and price variables, which allows us to disentangle the various channels and avoid the biases inherent in production function estimation without price data (De Loecker et al., 2016).

3 Empirical Facts

This section presents a set of empirical stylized facts on firms' monopsony power and research activities that guides our theoretical analysis. Section 3.1 presents the data. Section 3.2 describes how we estimate firms' monopsony power based on the production function approach (e.g., Dobbelaere and Mairesse (2013)) and subsequent work). Section 3.3 presents the key empirical facts.

3.1 German manufacturing firm-level data

Our main empirical analysis is based on the *AFiD* data, an administrative and representative panel of German manufacturing firms covering the years 1995-2018.[2] The data is collected and provided by the German statistical offices and comprises all manufacturing firms with at least 20 employees. The data includes information on firms' employment, outputs, input expenditures, investment, including R&D expenditures, and, most notably, output sales, quantities, and prices of firms' individual products, which allows us to address the "price-bias" when estimating labor market power and productivity (De Loecker et al., 2016; Bond et al., 2021). While core variables, such as sales and employment, are available for the full population of firms with at least 20 employees, other variables are only available for a representative 40% sample, which is redrawn roughly every 4 years. We use this subset for our analysis, as it contains information on firms' R&D expenditures as well as variables that are required to estimate firms' labor market power. As capital stocks are not directly observed in the data, we use a perpetual inventory method following Bräuer et al. (2023) that derives capital stocks by accumulating observed information on investments and depreciations.

Appendix Table A1 provides an overview on all variable definitions used in our article; Appendix Table A2 provides associated summary statistics for key variables separately for East and West Germany.[3]

[2] Access requests to the data can be made here: https://www.forschungsdatenzentrum.de/en/request. The files (DOI) we use are: 10.21242/42131.2017.00.03.1.1.0, 10.21242/42221.2018.00.01.1.1.0, and 10.21242/42111.2018.00.01.1.1.0.

[3] We clean firm-year observations that are in the bottom or top 0.5% tails of the distributions of value-added over revenue and revenue over labor, capital, intermediate input expenditures, and labor costs. We further eliminate quantity and price information for products displaying a price deviation from the average product price located in the top and bottom 1% tails. Moreover, we drop any non-manufacturing industries and the NACE rev. 1.1 manufacturing industries 16 (tobacco), 23 (coke, refined petroleum, and nuclear fuel), and 37 (recycling) due

3.2 Jointly estimation of labor market power and productivity

Labor market power. Our key question is how labor market power affects firms' incentives to invest into R&D. To derive our main measure of firms' labor market power, we follow an established literature that uses the so-called "production approach" to estimating labor market power (Dobbelaere and Mairesse, 2013; Mertens, 2022, 2021; Yeh et al., 2022). The attractive features of this approach are that it does not require specifying a labor market model, that it yields a firm-year-specific labor market power estimate, and that if allows for a joint measurement of firms' total factor productivity. As we discuss below, the approach, however, also relies on some strong assumptions. We therefore also show that alternative metrics of labor market power yield qualitatively similar results.

Firms manufacture output, Q_{it}, by combining labor, L_{it}, capital, K_{it}, and intermediates, M_{it}, using the production function:

$$Q_{it} = Q(.) = Q(L_{it}, K_{it}, M_{it})A_{it}. \tag{1}$$

A_{it} denotes firms' total factor productivity and is assumed to be Hicks-neutral and (we discuss this below). i and t index firms and years. We specify production in a general form and will later rely on a *translog* production function for the estimation. The only formal requirement is that $Q(.)$ is twice differentiable. Firms maximize profits:

$$\pi_{it} = P_{it}(Q_{it})Q_{it} - w_{it}(L_{it})L_{it} - r_{it}K_{it} - z_{it}M_{it}. \tag{2}$$

P_{it} denotes the output price. w_{it}, r_{it}, and z_{it} are the unit input costs for labor, capital, and intermediate inputs. Note that firms have wage-setting power resulting from upward sloping labor supply curves. Although we do not explicitly analyze product markups, we also allow firms to have price-setting product market power in Equation (2).

As shown in Appendix B, using the FOCs with respect to labor and intermediate inputs, we can derive a measure of the firm's labor market power, γ_{it}, defined as the wedge between the marginal revenue product of labor ($MRPL_{it} = \frac{\partial P_{it}(Q_{it})Q_{it}}{\partial L_{it}}$) and the wage:

$$\gamma_{it} = \frac{MRPL_{it}}{w_{it}} = 1 + \frac{1}{\varepsilon} = \frac{\theta^L_{st}}{\theta^M_{st}} \frac{z_{it}M_{it}}{w_{it}L_{it}}. \tag{3}$$

$\theta^X_{it} = \frac{\partial Q_{it}}{\partial X_{it}} \frac{X_{it}}{Q_{it}}$ denotes the output elasticits of input $X = \{L, M\}$. In a competitive setting, the wage equals the marginal revenue product of labor. If the firm has labor market power, it pays wages below the marginal revenue product.[4]

Estimating production functions and productivity. Measuring labor market power via Equation (3) requires estimates of the output elasticities of labor and intermediates. To recover

to an insufficient number of firms for estimating production functions.

[4] Our framework implies that $\gamma_{it} > 1$. Empirically, values of γ_{it} can be below unity, which can result from labor adjustment costs (Mertens and Schoefer (2024)). We discuss this further below and when presenting our empriical results.

output elasticities, we estimate firms' production function. This will also generate a measure of total factor productivity that we will utilize in our analysis to study. To estimate the production function, we apply an established control function based on seminal work by Olley and Pakes (1996) and Levinsohn and Petrin (2003). Specifically, we follow previous work using the same data by Mertens (2022) and Bräuer et al. (2023). Below we summarize the key steps of this approach, while we delegate a detailed description of the estimation routine to Appendix C.

We rely on a translog production function that allows for *firm- and time-specific* output elasticities:

$$\begin{aligned} q_{it} = \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \beta_{l2} l_{it}^2 + \beta_{k2} k_{it}^2 + \beta_{m2} m_{it}^2 + \\ \beta_{lk} l_{it} k_{it} + \beta_{lm} l_{it} m_{it} + \beta_{km} k_{it} m_{it} + \beta_{lkm} l_{it} k_{it} m_{it} + a_{it} + \epsilon_{it}. \end{aligned} \tag{4}$$

Lower-case letters denote logs. ϵ_{it} is an i.i.d. error term. We estimate Eq. (4) separately for each NACE rev. 1.1 industries using a version of the one-step approach by Wooldridge (2009), which defines a control function for unobserved productivity using information on firms' expenditures for raw materials and energy inputs while controlling for additional input demand shifters, such as export status or input prices (wages). As the literature has highlighted, estimating the production function with such an approach is typically subject to biased estimates as output and input prices of firms are unobserved and correlated with input decisions and output quantities (De Loecker et al., 2016). To account for firm-specific output price variation, we follow Eslava et al. (2004) and derive a firm-specific output price index from our firm-product-level price data that we use to deflate firm revenue, yielding a quasi-quantity measure of output (that we, with slightly abusing notation, denote by q_{it}). To control for unobserved input price variation (e.g., due to input quality variation), we rely on a firm-level adaptation of the approach proposed by De Loecker et al. (2016). Specifically, we formulate a firm-specific input price control function based on observed firm-product-level output prices and market shares that we add to the production function. Through this, we can control for input price variation, assuming that input prices and output prices are correlated which is the core idea in (De Loecker et al., 2016).

Having estimated the production function, we calculate output elasticities as $\theta_{it}^X = \frac{\partial q_{it}}{\partial x_{it}}$ and derive log productivity (TFP), a_{it}, as $a_{it} = q_{it} - \phi_{it}(l_{it}, k_{it}, m_{it})$, where $\phi_{it}(l_{it}, k_{it}, m_{it})$ captures the production factors and their interactions terms from Equation 4 (i.e., all terms except a_{it} and ϵ_{it}).[5] Importantly, as we clean output and input price variation in our estimation routine, our productivity measure can be viewed as a quantity-productivity measure, i.e., TFPQ. Estimated output elasticities from the production function are meaningful and in line with our expectations. Average capital, intermediate, and labor output elasticities equal 0.11, 0.64, and 0.30, respectively (see Appendix Tables A2).

[5]We explain in Appendix C how we use firm-specific price information to account for firm-specific input price differences as in De Loecker et al. (2016).

Discussion and Robustness: Hicks-neutrality. In line with prior work, the framework above assumes Hicks-neutral productivity to estimate labor market power and productivity. To address potential concerns regarding this assumption, we also use two alternative estimates of firms' monopsony power. First, we use regional labor market concentration indices as a simple measure of regional labor market power, which can be motivated by recent work connecting labor market concentration to monopsony power (Azar et al., 2022). Specifically, we calculate regional HHI-concentration indices for firms' wage bills. Second, we estimate firms' labor supply elasticity using wage and employment data. Given the absence of linked employer-employee data, we have to rely on firms' average wages, while controlling for workforce characteristics and a comprehensive set of firm-level observables. We estimate supply elasticities separately by regions and detail our estimation routine in Appendix D. While we prioritize the production function approach as our primary estimation method, we believe it is valuable to demonstrate that multiple approaches lead to similar conclusions regarding regional labor market power differences in the data.

To further validate our results based on productivity estimates (which are also based on the production function routine), we replicate key findings using a simple labor productivity measure, defined as the log of value added per employee. To account for variations in capital intensity, we regress these labor productivity measures on capital stocks per employee and use the residuals from this regression as our productivity estimates.

Discussion and Robustness: Adjustment costs and input timing Another potential concerns is that also adjustment costs create wedges between wages and marginal revenue products, which may bias our labor market power measure. Similarly, the production function approach depends on specific input timing assumptions. Estimating labor supply elasticities or using non-parametric labor market concentration indices as well as incorporating a non-parametric labor productivity measure in our analysis, as outlined in the previous paragraph, addresses these concerns as well.

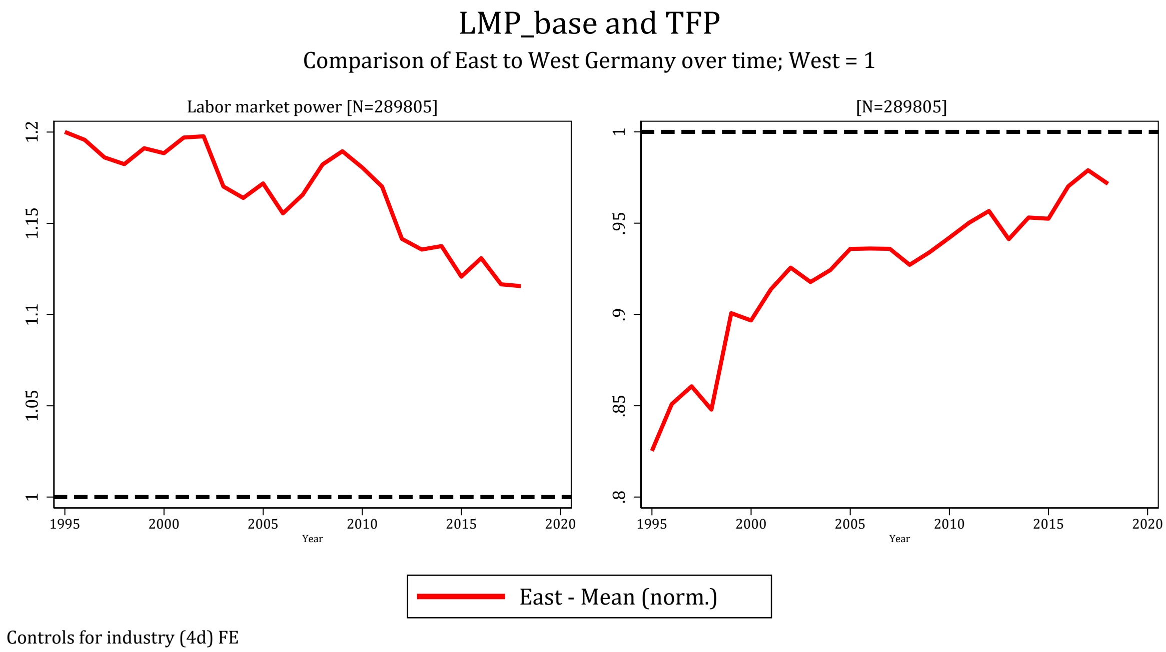
3.3 Empirical Facts

Fact 1: East German firms are less productive and have higher labor market power. Figure 1 reports the time series for average firm labor market power and firm-level total factor productivity (TFP) after residualizing four-digit industry fixed effects. The values are reported as East-German values relative to the West.[6] We document a significant productivity gap between West and East Germany, which, however, narrowed over our observation period. This reflects a well-known convergence process of East-Germany after the reunification. Convergence slowed down in the more recent years of our data, such that a sizeable productivity gap remains.

In addition to these persistent productivity differences, our data shows similar differences in

[6]Since this figure is not weighted by firm-size the productivity gap appears less severe, which is driven by small firms with high estimated TFP values, which however are less consequential in the aggregate productivity gap.

Figure 1: Labor market power and productivity differences



Notes: Evolution of avg. labor market power and TFP over time for East and West Germany. The West German level is normalized to 1. All graphs control for 2-digit industries to eliminate the effect of the different industry composition in East- and West Germany. Throughout our time period, labor market power is substantially higher in East Germany. *Source*: AFiD, own calculations

firms labor market power between East and West German firms. Mimicking the productivity patterns, differences in labor market power narrowed but remained significant in the latest years.

Fact 2: Firms with higher labor market power innovate less. Table 1 displays a set of regression results the correlate firms' R&D activity with firms' labor market power while controlling for firms' employment and capital stocks, and industry and year fixed effects. Column (1) shows that there is a strong negative correlation between LMP and R&D intensity. Given a standard deviation of LMP of 0.45 in the sample, an increase of LMP by one standard deviation corresponds to a 0.35 percentage point increase in the R&D expenditures as a share of sales, which is quite large considering that the overall average R&D intensity ranges from 1 to 3% in the sample. Columns (2)-(3) focus on the extensive and intensive margin. Column (2) replaces the dependent variable with a R&D-dummy variable measuring if the firm conducts any R&D. Columns (3) uses logged R&D expenditures, which excludes firms with zero R&D expenditures. We find that the negative effect of LMP on R&D itensity operates both, through the extensive and intensive margin. Effects on both margins are sizeable. Specifically, a 10% increase in LMP reduces R&D expenditures at the intensive margin by 1.6% and reduces the share of firms conducting R&D by 0.3 percentage points.

Fact 3: Smaller Eastern firms have a relatively high R&D-intensity, while large Eastern firms have a relatively low R&D intensity. While Fact 2 showed that LMP and R&D are generally negatively related, Figure 2 reveals interesting heterogeneities with respect to R&D

Table 1: R&D activity and LMP

VARIABLES	(1) R&D/sales	(2) R&D dummy	(3) log. R&D
Labor market power	-0.772***	-0.0367***	-0.164***
	(0.0482)	(0.00669)	(0.0327)
l	0.274***	0.111***	0.895***
	(0.0238)	(0.00369)	(0.0205)
k	0.322***	0.0444***	0.334***
	(0.0176)	(0.00266)	(0.0165)
Constant	-4.599***	-0.848***	2.941***
	(0.210)	(0.0285)	(0.179)
Observations	240,440	240,440	82,725
R-squared	0.226	0.297	0.625
Industry4d-Year FE	Yes	Yes	Yes
Firm FE	No	No	No
Firms	39245	39245	14844

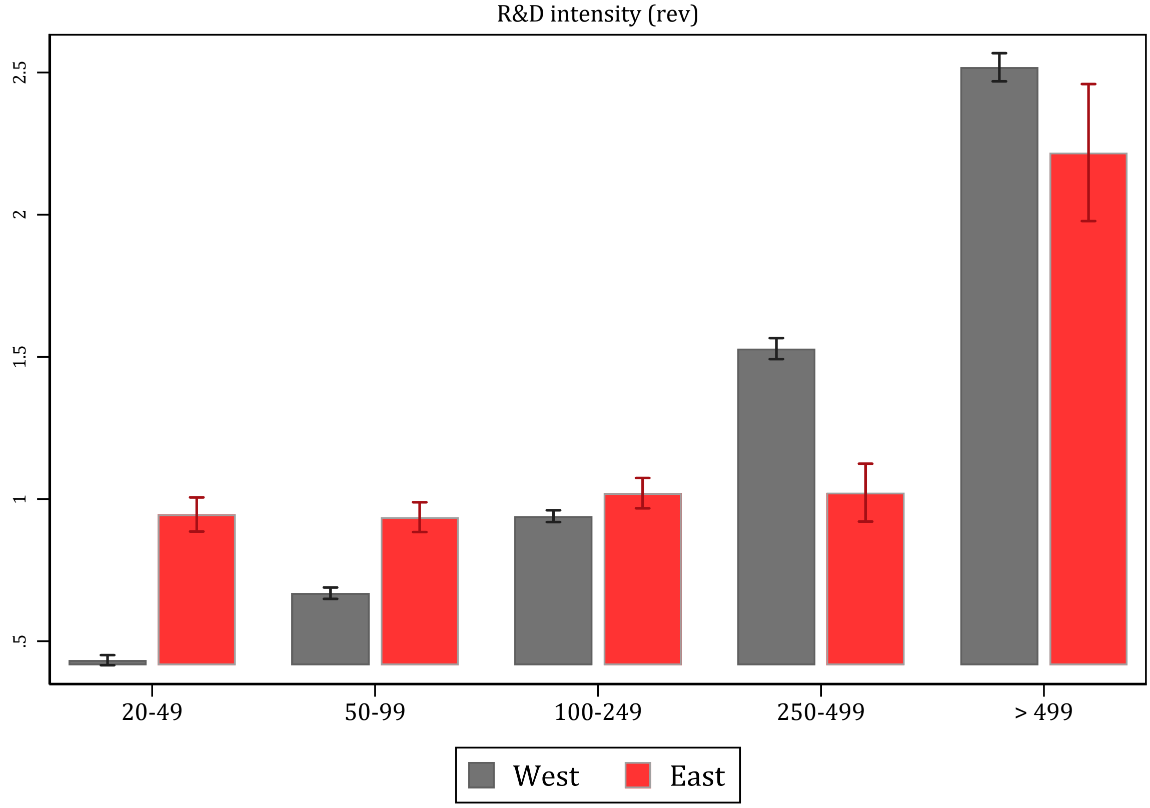
Model: base. Pooled OLS regression.
Clustered standard errors on firm level in parentheses.

investment across firm sizes. The figure reports average R&D intensities by size class. While Eastern firms, on average, invest less in R&D, small East German firms actually exhibit higher R&D intensities compared to their Western counterparts. Only when considering firms with more than 250 employees, we find that West German firms are more R&D intensive. Since larger firms typically exhibit higher R&D intensity in general and contribute the majority of overall R&D spending, the relatively small R&D activity in large firms and the general scarcity of large firms are key reasons why East Germany is lagging behind in innovation. In combination with the negative correlation of R&D with LMP and the generally higher LMP in East Germany (Fact 1), this finding is particularly interesting, and might indicate that small firms have higher returns from investing in R&D in the East in a high labor market power environment, while the opposite seems true for larger firms. Our model in Section 4 can generate these patterns and shows that labor market power affects the incentives to invest and growth differently for large (high-productivity) and small (low-productivity) firms.

Fact 4: Profit gains from increasing productivity are smaller for high-labor market power firms. Ultimately, we are interested in understanding how firms' incentives to conduct R&D and improve their productivity are shaped by labor market power. To better grasp these dynamics, Figure 3 show binned scatter plots from projecting profit shares in sales against productivity levels while controlling for industry-year fixed effects for firms across the LMP distribution that we observe. We define profits as sales revenues minus costs for labor, materials, and capital, where capital costs are proxied by an interest rate (r=0.03) times the capital stock. The result is qualitatively robust to specifying capital costs in different ways.

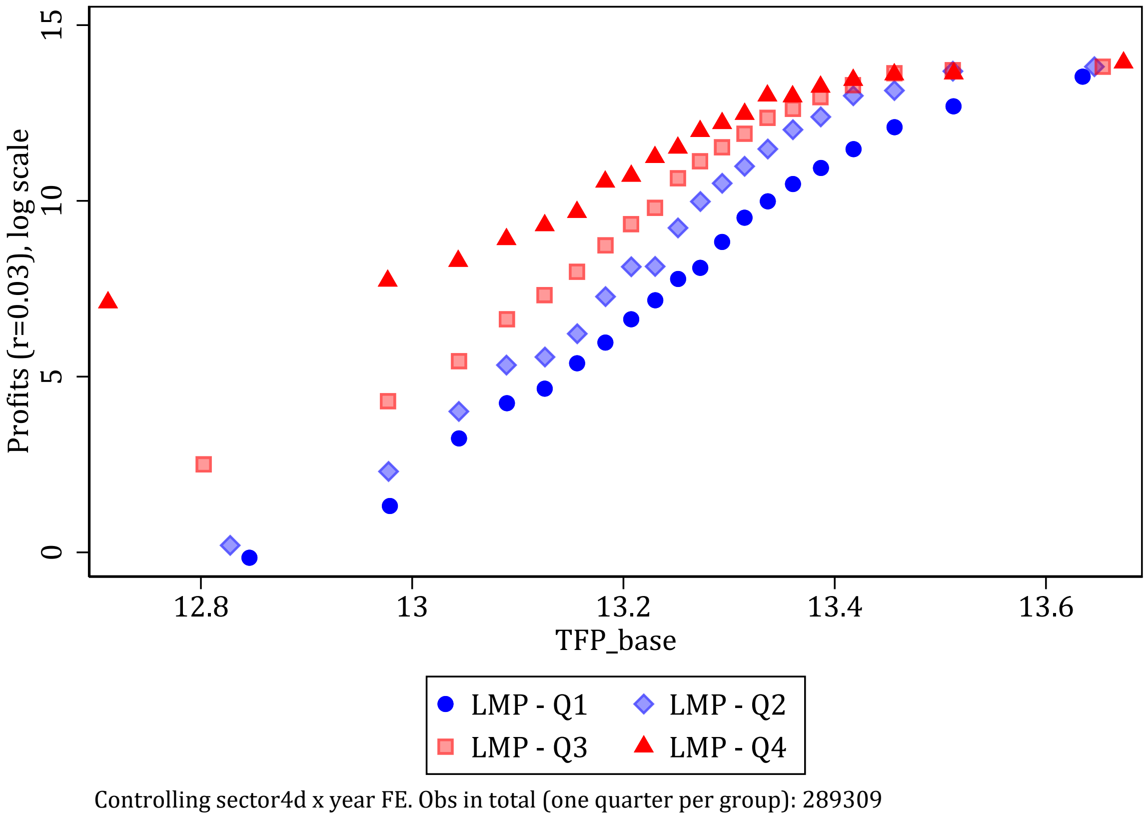
Firms with higher productivity levels generate greater profits. Also, LMP generally increases

Figure 2: R&D expenditures, by size class



Notes: This bar plot shows for different firm size classes the avg. R&D intensity (R&D / Sales in %) across all years. R&D intensity is higher at smaller Eastern firms and lags behind the West predominantly for larger firms. *Source*: AFiD, own calculations

Figure 3: Productivity and profits under different LMP regimes



Notes: Binscatter plots showing the relationship of profits (with profits equal to revenues minus labor costs, material costs and a proxy for capital costs computed as $0.03 \cdot capital$) with firm TFP. Profits may include negative profits as well and are shown on a log scale on the y-axis. The dotted lines are drawn for four quartiles of LMP, where Q1 is the lowest and Q4 the highest quartile. The plot shows that while LMP is generally leading to higher profits at almost any TFP level, the relationship between the two is much weaker for high LMP firms: Profits rise considerably less for a high LMP firm compared to a low LMP firm if TFP is increased. The plot features only 4-digit industry X year fixed effects as controls. *Source*: AFiD, own calculations profits: The curves of the higher LMP quartiles are above the curves of lower LMP quartiles. However, there is an important difference regarding the slopes of these curves: The Profit-TFP relationship is considerably flatter for high labor market power firms. Hence, at lower levels of productivity, high labor market power firms generate relatively higher profits. This marginal proft-advantage diminishes relative to low labor market power firms at higher productivity levels. This suggests that the returns from increasing productivity are less substantial for high labor market power firms. Intuitively, an increase in productivity prompts firms to expand their size. Firms with higher labor market power are however incentivized to operate at relatively lower optimal size to reduce wages and increase profits. This decreases their gains from expanding and thus investing into higher productivity. Our model will incorporate this intution to rationalize this striking fact of the data.

Summary. Overall, we find that labor market power is higher in structurally weaker regions characterized by lower productivity (Fact 1). These regions are concentrated in East Germany. Higher labor market power is also associated with lower R&D investment (Fact 2). Small (large) firms active in regions with higher (lower) labor market power invest more in R&D (Fact 3). Consistent with that, firms with higher labor market power experience larger (smaller) gains from increasing productivity at low (high) productivity levels (Fact 4). Motivate by these stylized facts, we will now develop a dynamic innovation model that can replicate our empirical findings.

4 Theoretical framework

To understand the aggregate implications of our empirical results, we build an endogenous growth model where firms have labor market power. Appendix F provides more details on the derivations.

4.1 Household Preferences

We consider a setting in which workers choose a firm to work for within one of several labor markets. Some of these labor markets are more competitive than others. This follows the classic nested logit structure, where nests correspond to regions and choices within nests correspond to firms. It is known that this class of models can be microfounded with randomly drawn taste shocks since McFadden (1978, 1981). Cardell (1997) offers a closed form of one of the shock distributions that create this behavior, but it is so complicated as to obscure more than illuminate critical assumptions. We mix taste shocks and congestion externalities, two staples of the economic geography literature, to provide a much simpler motivation for the same choice structure. However, there are whole classes of models with observationally equivalent choice behavior to our own.

We consider a continuous-time economy divided into multiple labor markets. Households gain utility according to

$$
\begin{aligned}
U = \int_0^\infty e^{-\rho t} \ln(U_i(t))\, dt &= \int_0^\infty e^{-\rho t} \ln\Big(w_f \, \left[\tilde{\varepsilon}_{i,f} \frac{s_c}{s_R} \right]^{\varepsilon_R} \Big)\, dt \\
&= \int_0^\infty e^{-\rho t} \left[\ln w_f \; + \; \varepsilon_R (\ln \tilde{\varepsilon}_{i,f} + \ln(s_c/s_R)) \right]\, dt
\end{aligned}
\tag{5}
$$

ρ is the time preference parameter, $c_i(t)$ denotes consumption of the final good at time t, which also serves as the numéraire and is also used for R&D investment as discussed below. w_f is the firm wage, $\tilde{\varepsilon}_{i,f} \sim$ Fréchet$(\alpha = 1,\, s = e^{-\gamma})$ is a multiplicative taste idiosyncratic shock that each worker draws for every firm, s_R is the regions labor share, s_c is the labor share in the baseline final-goods sector, and ε_R is the weight of the non-monetary components of utility. If ε_R is high, workers value the differences between firms and regions more highly and thus labor market power is higher. If $\varepsilon_R = 0$, workers only care about the highest wage and there is no labor market power.

We intentionally capture all sources of labor market power in one parameter and are agnostic as to what exactly this parameter represents. As in our empirical setting, we remain agnostic about the underlying causes of labor market power: We interpret these taste shocks broadly, encompassing geographic immobility, occupation-specific preferences, switching costs, and frictions in job matching – factors that collectively generate labor market power. Throughout the rest of the paper, we stick to the regional interpretation of nests for ease of exposition and to be easily comparable to other literature, which often does the same. However, both these papers and our model are not restricted to this interpretation. The final goods sector counts as its own nest indexed as $R = c$.

If the nests correspond to geographic regions, regions with high ε_R have high travel costs and thus both bigger cost shocks and higher congestion around desired areas. If nests represent occupations or tasks, higher ε_R occupations are ones where the exact fit between job and worker is more important and utility diminishes if the occupation is crowded and jobs become more 'standard'. To streamline notation, we use ε_R for the shape parameter and $\tilde{\varepsilon}_i(f_i, t)$ for individual draws. However, we will mostly be using ε_R from now on. Empirically, we find substantial spatial heterogeneity of ε_R: Labor market power is systematically higher in countries' poorer regions.

Although we refer to our nests as regions, the same structure could represent industries, occupations, or any other grouping that workers value. As in our empirical setting, we remain agnostic about the underlying causes of labor market power: We interpret these taste shocks broadly, encompassing geographic immobility, occupation-specific preferences, switching costs, and frictions in job matching – factors that collectively generate labor market power. Throughout the rest of the paper, we stick to the regional interpretation of nests for ease of exposition and to be easily comparable to other literature, which often does the same. However, both these papers and our model are not restricted to this interpretation. The final goods sector counts as its own nest indexed as $R = c$. Due to these two types of utility shocks, workers have preferences about working for specific firms (and the final goods sector).

4.2 Final Good Production

The final good is produced with labor and intermediate inputs according to

$$Y(t) = L_c^{\beta}\left(\frac{1}{1-\beta}\right)\int_0^1 A_j^{\beta}k_j^{1-\beta}\,dj \tag{6}$$

where j indexes the intermediate products, k_j is the quantity of variety j and A_j is its quality. β is the Cobb-Douglas parameter describing the importance of the final goods sector employment L_c and quality vs. the quantity of intermediate inputs. There is perfect competition in the final goods sector on both the labor and the product market side: $\varepsilon_c = 0$, i.e. workers do not experience idiosyncratic taste shocks or congestion externalities in this sector. Likewise, firms take prices of intermediate and final goods as given.

4.3 Intermediate goods Production and R&D

Intermediate goods are produced by specialized firms, each of which produces one variety. They produce with linear technology $k_j = \bar{A} \cdot l_j$, with $\bar{A}$ denoting the average technology in the economy. Specifically, we assume that $\bar{A} = \frac{Y}{L_c}$, i.e. $\bar{A}$ is a weighted average of the quality of all products (which determine the productivity of the final goods sector).[7] Thus, there are positive externalities from innovation to other intermediate producers. Producers of the same variety face Bertrand competition from each other and have to pay an infinitesimally small fee to produce. This setup follows (Akcigit and Kerr, 2018)

Only the firm that foresees winning the Bertrand competition will pay this fee, thus it will be the monopolist in the actual market. For simplicity, we let A_j, π_j, l_j etc. denote the technology, profits and employment of the equilibrium producer and drop the firm subindex.

Technology for every product is defined by its continuous product quality A_j. Firms increase the quality of their product with discrete innovations, each of which increases productivity by $\bar{A} * \lambda$. The step size of innovations is thus dependent on the average technology level in the economy and every innovation produces positive externalities on other firms. Firms spend R&D expenditures to increase the arrival rate of such innovations. Specifically, the costs to achieve a given arrival rate are

$$R(z_j, A_j) = \hat{\chi} * z_j^{\hat{\psi}} A_j \tag{7}$$

Expenditures $R(z_j, A_j)$ rise linearly with the current technology level of the firm A_j and even faster with the achieved rate of inventions z_j (since $\psi > 1$). The concave cost function ensures an interior solution for the optimal rate of innovations exists, independent of the actual value function.

Both R&D expenditures and productivity gains from innovation rise linearly in A_j, so if the firm value function were linear, all firms would have the same R&D intensity. However, con-

[7]The literature usually just assumes $\bar{A} = \int a_j$. However, this is a smaller difference than first appears, since in these simpler models, each quality enters linearly into $\frac{Y}{L_c}$

trary to the earlier literature, this is not generally the case in our model due to the distorting presence of labor market power.

If there is no innovation, firm productivity still changes due to technology diffusion. This feature of our model captures the empirically observed regression of firm productivity towards the mean. Specifically, we assume that

$$z_j^{dif} = \phi; \Delta^{dif} A_j = (1 - \frac{A_j}{\bar{A}})\lambda \tag{8}$$

where parameter *phi* determines the rate at which innovations diffuse to the firm and the innovation size depends on the distance to the average productivity and the innovation step size parameter λ.

4.4 Entry and Exit

We assume that there is a mass of potential entrants in each region that invest to make product innovations and replace an intermediate producer. The cost of creating new firms is

$$C_{e,R}(x_{e,R}, \bar{A}) = \nu * x_{e,R}^{\xi} \cdot \bar{A} = \nu * (\frac{\delta_{e,R}}{M_{f \in R}})^{\xi} \cdot \bar{A} \tag{9}$$

where $x_{e,R}$ is the arrival rate of new firms in region R, which is equivalent to the exit rate of old firms. Research is undirected within region, i.e. an entrant replaces a random firm in the region. Thus, the entry rate is linked closely to (from the viewpoint of the incumbent firm) exogenous regional exit rate $\delta_{e,R}$ via the mass of firms in region R $M_{f \in R}$. $\bar{A}$ is the average product quality in the economy and ν and ξ are model parameters that capture the 'production function' of entrepreneurship. With high ξ, higher expected values of firms will have a more limited impact on the number of new firms, since the costs of creating new firms rises quickly. We think of these parameters as describing the depth and width of the pool of potential entrepreneurs.

4.5 Equilibrium

Labor Supply

Workers first choose a region and then a firm within that region. Within each region (or nest more generally), workers will draw a Fréchet shock for each firm and then choose the best combination of wage and taste shock. Free movement between regions forces equalizes expected utility between regions, which governs the size of all nests. Note that the final goods sector is its own nest. As is standard in the literature, the Fréchet distributed shocks yield closed form solutions both for expected utility per nest and the probability for choosing each firm, given that the worker is already committed to region R. It will be useful to express labor supply to firm f relative to the final goods sector. Specifically,

$$l_f = p(f) \cdot \bar{L} = p(f|R) \cdot \frac{p(R)}{p(c)} \cdot p(c) \cdot \bar{L} = \frac{w_f^{\frac{1}{\varepsilon_R}}}{\mathbf{W}_R} \cdot \frac{\mathbf{W}_R}{w_c^{1/\varepsilon_R}} \cdot L_c = \left(\frac{w_f}{w_c}\right)^{\frac{1}{\varepsilon_R}} \cdot L_c \tag{10}$$

The employment in each firm is determined by the ratio of the wage relative to the competitive wage in the final goods sector, taken to the power of the inverse labor market power parameter ε_R. If labor market power is low, even small deviations from the competitive wage will already create strong employment effect (because workers do not value the non monetary parts of utility very highly). The regional wage index $\mathbf{W}_R \equiv \int_{f' \in R} w_{f'}^{\frac{1}{\varepsilon_R}} \, df'$ cancels out, i.e. firms do not need to consider what the other firms in their region are doing, they can compare themselves to the final goods sector only. A higher regional wage index attracts more workers to the region, but the share of the firm in the region will decline proportionally. Derivations are detailed in Appendix F.

Rearranging eq. (10) gives the wage of firm f as a function of its size:

$$w_f = w_c \left(\frac{l_f}{L_c}\right)^{\varepsilon_R} \tag{11}$$

So a firms' labor supply is the competitive wage, multiplied with its quasi employment share $\frac{l_f}{L_c}$ to the power of ε_R. This is very close to the existing literature on labor market power, except that the size of the local labor market is not given by a fixed labor supply $\bar{L}$ since there are multiple nests. Instead, firm size is relative to the benchmark nest c.

The above implies that the wage elasticity that each intermediate goods firm faces is constant ($\frac{\partial w}{\partial l} \frac{l}{w} = \varepsilon_R$).

Final Goods Sector

Profit maximization by the atomistic firms in the final goods sector yields then inverse demand function for each intermediate input j:

$$p_j = L_c^{\beta} A_j^{\beta} k_j^{-\beta} \tag{12}$$

Each variety is produced by only one intermediate firm in equilibrium: Producers of the same variety face Bertrand competition from each other and have to pay an infinitesimally small fee to produce. Only the firm that foresees winning the Bertrand competition will pay this fee, thus it will be the monopolist in the actual market. This is as in (Akcigit and Kerr, 2018). For simplicity, we let A_j, π_j, l_j etc. denote the technology, profits and employment of the equilibrium producer and drop the firm subindex, except when discussing the competition between entrant and incumbent upon firm entry.

Inserting optimal product demand (eq. 12) back into the production function, and solving for optimal labor demand of the final good sector (L_c), we get

$$w_c = \beta \cdot \bar{A} \tag{13}$$

I.e. the final goods sector will hire more workers until the competitive wage is driven up to $\beta \cdot \bar{A}$ and the wage share of the final goods sector is β.

Intermediate firms

Taking into account the demand they face (eq. 12), the wage benchmark set by the final goods sector (eq. 13) and their labor supply curve (eq. 10), a firm producing variety j will choose their optimal labor input to maximize profits.

$$l_j^* = \left[\frac{(1-\beta)}{(1+\varepsilon_R)} \cdot \left(\frac{A_j}{\bar{A}}\right)^{\beta} \left(\frac{1}{\beta}\right) \right]^{\frac{1}{\beta+\varepsilon_R}} \cdot L_c \tag{14}$$

Firms sizes is a function of of the final goods production function parameter β, the labor market power parameter ε_R and firm productivity A_j over average productivity $\bar{A}$. Firms are larger the more productive they are. The effect of labor market power on firm size is ambigous: Labor market power increases firms' wage gradient, making it more expensive to hire additional workers. However, it also lowers level of initial wages: If workers have strong idiosyncratic preferences, the first workers will be willing to work for extremely low wages. For very unproductive firms, the latter effect dominates. The more productive (and larger) the firm gets, the more the increased gradient will dominate and firms will find it optimal to reduce their size relative to a competitive situation to keep wages low.

This strategy will result in profits of

$$\pi_j = L_c \cdot A_j \cdot \left(\frac{\bar{A}}{A_j}\right)^{\frac{\varepsilon_R(1-\beta)}{\beta+\varepsilon_R}} \cdot \frac{1}{\beta}^{\frac{(1-\beta)}{\beta+\varepsilon_R}} \left[\left[\frac{(1-\beta)}{(1+\varepsilon_R)}\right]^{\frac{1-\beta}{\beta+\varepsilon_R}} - \left[\frac{(1-\beta)}{(1+\varepsilon_R)}\right]^{\frac{1+\varepsilon_R}{\beta+\varepsilon_R}} \right] \tag{15}$$

Profits are a function of the final goods production function parameter β, the labor market power parameter ε_R, firm productivity parameter A_j and average productivity $\bar{A}$. They are also scaled by the size of the final goods sector, $_c$. Note that π_j are linear in firm productivity if $\varepsilon_R = 0$, in which case the model collapses to (Akcigit and Kerr, 2018), which has no labor market power. Note that the effect of ε_R on profits need not be positive: If a firm is very productive, its wage $w_c(\frac{l_j}{L_c})^{\varepsilon_R}$ can exceed the wage it would have paid in a competitive market: As it tries to attract workers away from firms where they have high taste shocks, it will have to pay increasingly higher wages and would have preferred a competitive market.

Labor market equilibrium

To determine scaling factor L_c, we use that free mobility between regions fixes the relative size off all regions (eq. 10). Since all shares add up to one

$$s_c = \frac{1}{1 + \sum_{R \neq c} \left[\frac{(1-\beta)}{\beta(1+\varepsilon_R)} \right]^{\frac{1}{\beta+\varepsilon_R}} \int_{j \in R} \left(\frac{A_j}{\bar{A}} \right)^{\frac{\beta}{\beta+\varepsilon_R}}} \tag{16}$$

I.e. the share of the final goods sector is endogeneous, not only driven by the distribution of ε_R across regions, but also the number of firms and their productivity relative to the average. However, the labor share of the final goods sector will be constant on the steady state growth path.

Incumbent R&D decision

Combining static profits and the innovation costs, the HJB-equation of the firm's optimization problem is:

$$\begin{aligned} r * V(A_j, \varepsilon, \bar{A}) - \dot{V}(A_j, \varepsilon, \bar{A}) = & \pi^* * A_j^{\frac{\beta(1+\varepsilon)}{\varepsilon+\beta}} - R(z_j, A_j) \\ & + z_j[V((\lambda+1) * A_j, \varepsilon, \bar{A}) - V(A_j, \varepsilon, \bar{A})] \\ & + \phi[V((\lambda_\phi+1) * A_j, \varepsilon, \bar{A}) - V(A_j, \varepsilon, \bar{A})] \end{aligned}$$

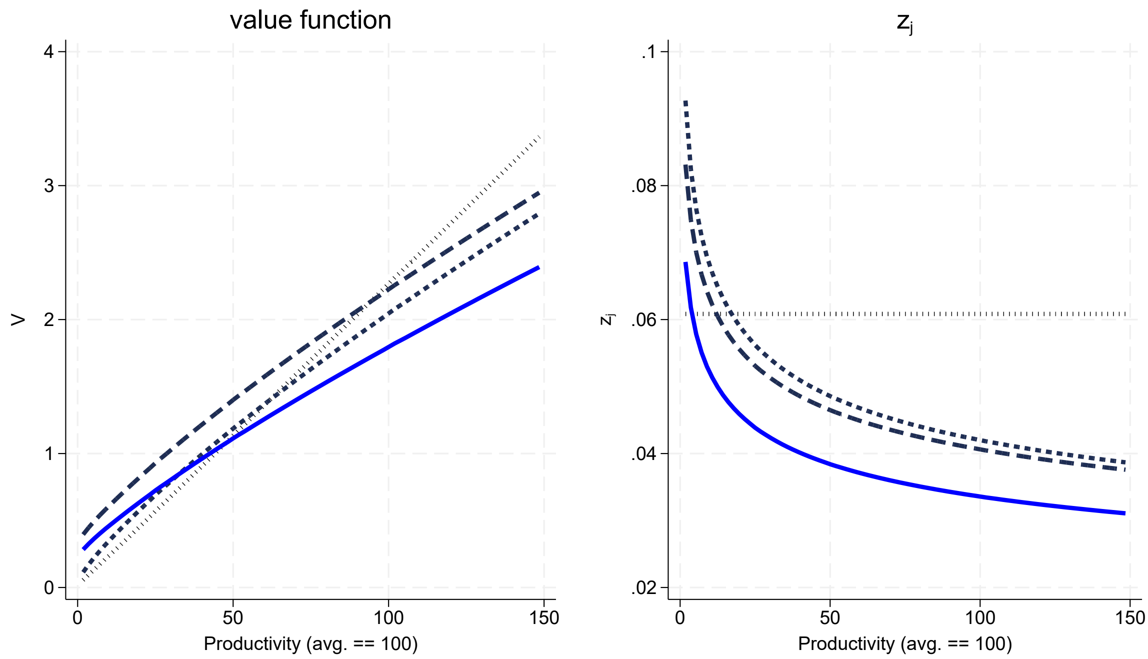
where the value of the firm is first driven by the current profits $\pi^* * A_j^{\frac{\beta(1+\varepsilon)}{\varepsilon+\beta}}$ and the costs of R&D $R(z_j, \bar{A})$. In addition, innovations arrive at rate z_j and diffusion events at rate ϕ, both of which increase A_j. Note that it is not generally possible to assume that $\dot{V}(A_j, \varepsilon, \bar{A}) = 0$, since even on the balanced growth path, $\bar{A}$ is growing. However, because of the non-linearity of profits, it is not enough to assume the economy is in steady state ($\dot{V}(A_j) = 0$) to solve the problem analytically. Thus, we are not able to solve the value function analytically.

However, our model does contain the standard model as a special case (if $\varepsilon = \phi = 0$), which has an analytical solution. It is illustrative to compare this previous model and special case to different deviations. Figure 4 present this comparison: Firms with labor market power and low productivity are more valuable than their competitive counterparts but they converge, but higher productivity firms will eventually be hindered by their tight labor markets. Thus, the value function is flatter than in the competitive case except for small firms. The innovation rate reflects this: Unproductive/small firms with labor market power are more innovative, but all other firms are less innovative, the more labor market power they have.

Entry and Exit

Upon Entry, an entrant and an incumbent can produce the same variety j. To understand which one 'wins' the competition, we need to compute the zero profit condition for both firms and then see which of these two packages would be more attractive to the final goods sector. In our baseline specification, we assume a pool of entrepreneurs in each region that also target firms within the same region, so that both incumbent and entrant have the same

Figure 4: Value and R&D for firms with different productivity



Notes: Value functions $V(A_j, \bar{A}, \varepsilon_R)$ and innovation arrival rate z_j for different special cases of the model: the linear case without labor market power, technology diffusion or entry (dotted) as a baseline, with added labor market power (short dashes), additionally with diffusion (dashed) and finally also with entry (blue). *Source*: AFiD, own calculations

labor market power. In this case, the incumbent knows it cannot outcompete the entrant with a higher quality product and leaves the market. Appendix F discusses the outcome if the incumbent has higher labor market power than the entrant.

5 Quantitative analysis

The implications of labor market power in a full endogenous growth model are complex: There is a direct static effect on allocative efficiency, a dynamic disincentive effect on incumbent R&D, a positive effect on entry and a misallocation effect on entry as entrepreneurs target regions with higher labor market power (and lower productivity). To understand how these forces interact, we calibrate our model to recapture the performance of Germany from 1995 (when our microdata starts) to 2020. We then simulate the counterfactual economy without labor market power.

5.1 Algorithm

To solve the equilibrium described in section 4, we use the fact that only the equilibrium growth rate and the rate of creative destruction/entry affect the firms' innovation decision, while e.g. the productivity distribution or other micro-moments do not matter to the firms. Thus, we can adapt a numerical strategy that will also find equilibria outside of the balanced growth path. This is potentially important since we cannot guarantee that the economy was in equilibrium when we observe it. This is especially true for the German case, where our data starts only 5 years after reunification and the former communist regions were certainly outside of equilibrium. Concretely, we follow these computational steps for each consecutive year:

- Guess a growth rate and endogenous entry rate
  - compute the static equilibrium, i.e. eq. (10)-(16)
  - use contraction mapping (on $\frac{V(A_j,\varepsilon,\bar{A})}{A_j}$) to solve the value function and incumbent firm innovation strategy
  - compute the equilibrium efforts by entrants, given the value of firms in each region
  - compute the implied growth rate
  - confirm that the computed growth and innovation rate match the guess, otherwise iterate

5.2 Calibration

Our rich model has the advantage that we can use microeconometrics to fix some of our parameters outside of the calibration and that we can target distributions in our microdata instead of our outcome of interest (aggregate variables) for the others. Specifically, we estimate labor market power differences in the micro data (see section 3), so we do not calibrate our labor market power parameters to explain the entire gap between East and West Germany. We are not as able to rely on our microdata when describing innovation related parameters: Measuring entry and innovation efforts and their effects in micro data is generally fraught with measurement error and identification problems. Only the cost curvature parameter ψ has been reliably estimated in micro data, with Griliches (1979); Blundell et al. (2002); Hall and Ziedonis (2001) all placing it around 2 (or rather, its inverse at around 0.5). We use that parameter for the curvature of entry efforts ξ as well. This leaves us with the technology diffusion, innovation step size and innovation and entry cost parameters. With these, we target the firm productivity distribution of East and West Germany in 2020 and the entry/exit rate. Table 2 gives an overview over our parameter values and their source.

Our simulated economy tracks the actual development of the German economy reasonably well: We start with an East German productivity distribution at roughly 80% of West Germany, with only negligible convergence over the next 25 years. The dispersion of productivity jointly identifies technology diffusion ϕ, innovation step size λ and innovation costs χ: Larger innovation step size and lower innovation costs would increase productivity dispersion via innovation within each region. They also decrease convergence, since they exacerbate the difference in R&D intensity between East and West Germany. A higher technology diffusion parameter ϕ would decrease productivity dispersion and lead to higher convergence, since less productive East German firms would passively learn via technology diffusion.

Table 2: Calibration of Model Parameters

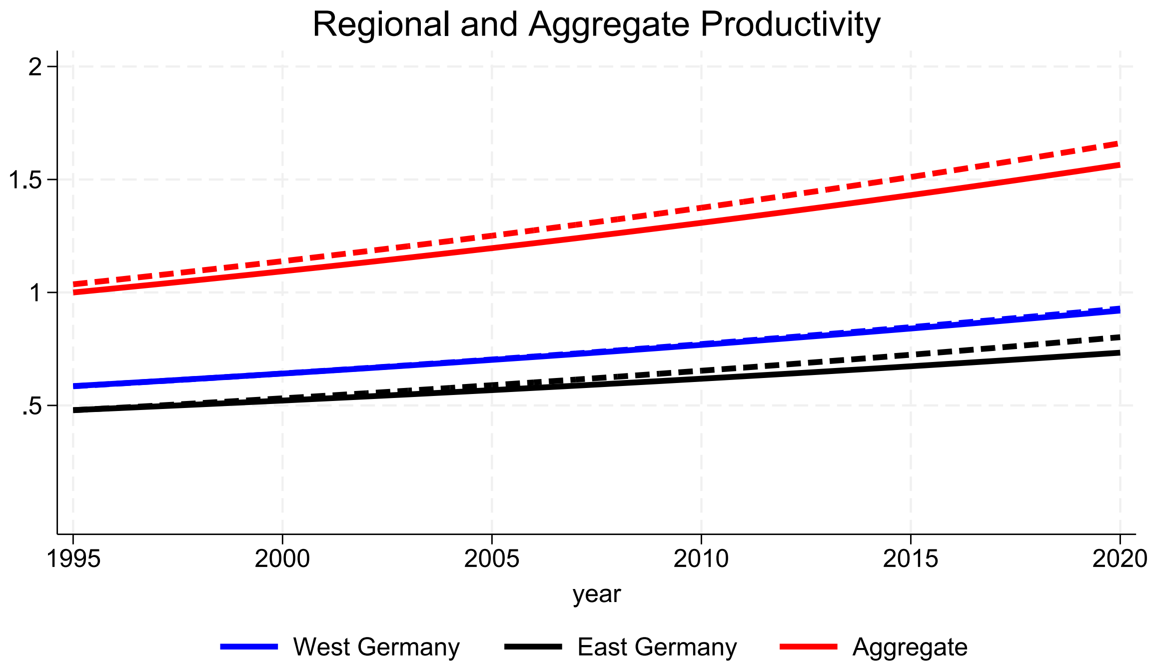
Parameter	Description	Identification	Value
β	Output elasticity of innovating firms in final goods production	Fitted	0.40
χ	Fixed cost of R&D investment	Fitted	10
λ	Innovation step size (productivity gain per innovation)	Fitted	0.30
ϕ	Mean-reversion rate of firm productivity	Fitted	0.02
ν	Fixed entry cost for new firms	Fitted	60
ψ	Curvature of R&D cost function	Literature (Griliches, 1979; Blundell et al., 2002; Hall and Ziedonis, 2001)	2
ξ	Curvature of entry cost function	set to curvature of R&D	2
ε^E	Labor supply elasticity (East)	Estimated (Section 3)	0.20
ε^W	Labor supply elasticity (West)	Estimated (Section 3)	0.00

5.3 Counterfactual Analysis

We run our counterfactual simulation over 25 years, covering the time period between 1995 (when our data starts) and 2020. Figure 5 shows the evolution of aggregate productivity and average firm productivity in both East and West Germany for the fitted and the counterfactual economy. In these 25 years, our simulated economy grew by 1.8% per year, while a counterfactual economy without labor market power grew by 2% per year. This additional growth comes mainly from the higher innovation investment of East German firms, which no longer have market power. The spillover to West German firms is negligible, though they also invest slightly more into R&D. In the counterfactual, the economy makes an immediate 3.6% productivity jump when setting labor market power to 0 because static inefficiencies are resolved. However, it takes a substantial amount of time before the (unweighted) average firm productivity in each region changes due to higher R&D investments. The initial decrease in labor market power also decreases the value of being a firm in that region and thus depresses entry, which is not decisive with our fitted parameters, since German entrants are only circa 5% more productive than existing firms. This effect is further mitigated since incumbent firms will increase their R&D investment when they see that the rate of creative destruction is going down.

From this, we conclude that labor market power can explain roughly 25% of the productivity gap between East and West Germany in 2020. It is important to note that removing labor market power in East Germany would also make the region more attractive and so not only raise productivity, but also give it a higher share of overall employment. In our baseline

Figure 5: Aggregate Productivity and avg. Firm Productivity within each region



Notes: Evolution of aggregate productivity (red), West German avg. firm productivity (blue) and East German avg. firm productivity (black), both with observed levels of labor market power (solid) and with no labor market power (dashed). *Source*: own simulations

specification, this is a substantial effect and we estimate the regional share of employment to be 3 percentage points higher in 2020.

6 Relevance Beyond the German Context

While the case of East and West Germany is a particularly fertile setting to study firm- and region-level differences in labor market power, innovation and productivity, we do not view our mechanism as a phenomenon specific to Germany. Many other countries face severe regional differences in GDP per capita, and in the following we briefly present evidence that these differences are correlated with the extent of firm labor market power. To do so, we use the 9th vintage data from the Competitiveness Research Network (henceforth, CompNet data) at the NUTS2 and NUTS3 regional level.[8] The data contains regional data on labor productivity (value added per employee), R&D expenditures, and labor market power (derived from estimating firms' production functions similar to our estimation) for various European countries.[9]

Using the CompNet data, Figure 6 shows for three other large European countries that labor market power is an important predictor of productivity differences within countries at the NUTS2 (or NUTS3) regional level. We can show this only for these larger countries in

[8]For details on the CompNet data, please see CompNet (2023).
[9]The data is based on firm-level data and regional values are assigned based on headquarters.

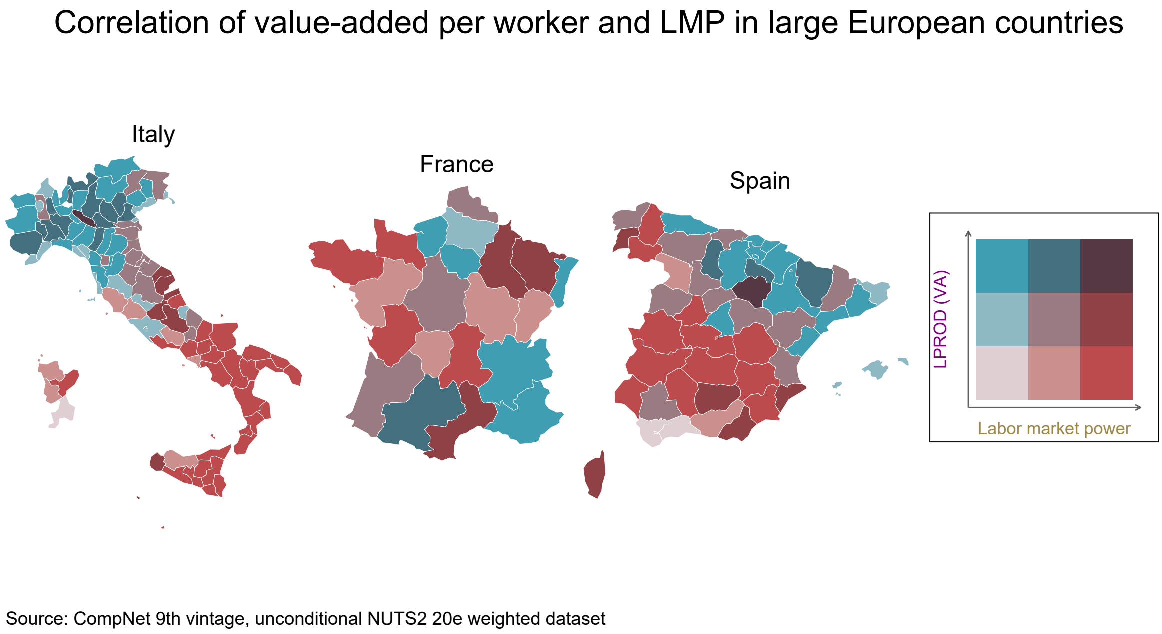


Figure 6: Labor market power and labor productivity in large European countries

CompNet as this exercise requires sufficient variation at the NUTS2 level to be meaningful.[10] We categorize value-added per worker and average labor market power in terms of within-country terciles. There is a clear negative correlation between the two variables, indicated by the colors on the diagonal between starkly blue and starkly red. In fact, almost all regions support the negative correlation between labor market power and labor productivity. Consequently, high firm labor market power is particularly prevalent in structurally weaker regions. Most notably, in Italy, where the North-South differences in economic development are similarly well-documented as in the German West-East case, the picture is closely in line with our descriptive results for Germany. We view this as strong out-of-context evidence supporting the validity of the mechanism we put forward in our paper.

To further highlight the relevance of labor market power in affecting productivity, Figure 7 presents regression results using CompNet data across all European countries. Here, average firm labor productivity, measured as log sales per worker as in our study in Section 3, and average R&D expenditures are regressed on average labor market power at the regional level. The significant negative correlation between labor market power and productivity or R&D is consistent with our view that labor market power is a potential factor hampering innovation, productivity growth, and thus GDP per capita growth and convergence across European regions.

7 Conclusion

Labor market power is an important and persisting friction, especially in structurally weak regions in advanced economies. Beyond its well-documented negative effect on wages and

[10]Unfortunately, the CompNet data does not include NUTS2 information for Germany.

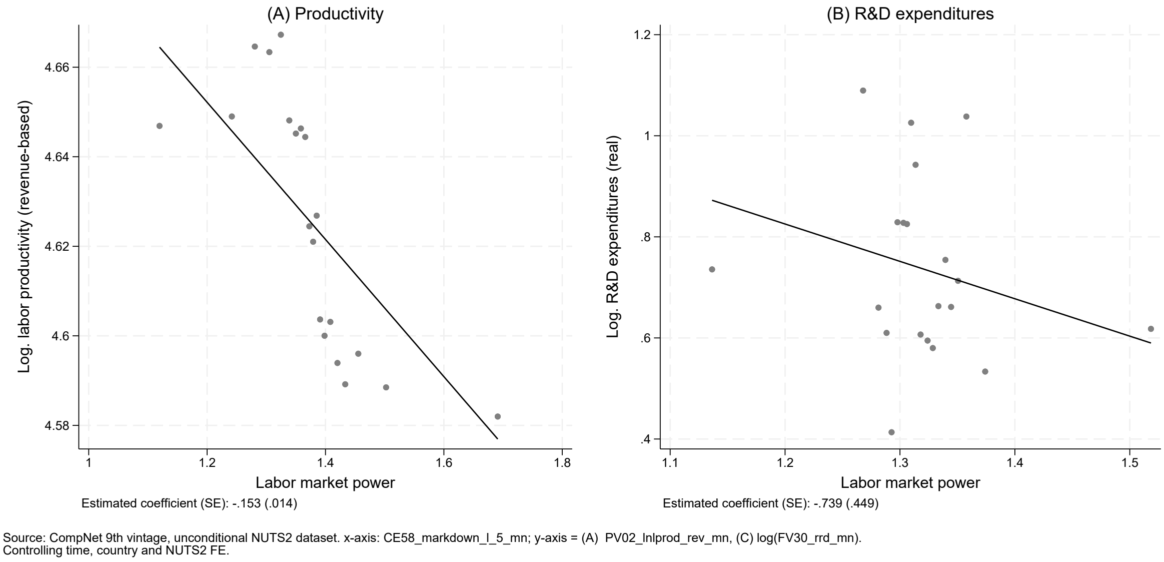


Figure 7: Labor market power, productivity and R&D across regions in 19 European countries

output, we show how labor market power can influence firms' decision to conduct R&D and entrepreneurs' decision to enter the market in a unified endogenous growth model framework. We propose that this can explain the missing convergence between rich and poor regions within European countries. We study the German situation in the most detail, where East Germany is not catching up to West Germany, whether in terms of productivity, wages and GDP.

To study the relationship between labor market power and productivity-enhancing R&D investments of firms, we build an endogenous growth model with R&D investments, entry, technology diffusion and regional labor markets with different levels of labor market power. We calibrate this model using rich German manufacturing-sector firm-level panel data that allows us to measure firms' R&D activity and to estimate state-of-the-art measures of firm-specific labor market power and total factor productivity. We establish several novel facts on firms' labor market power: Most notably, we show that small low-productivity firms have higher R&D investment rates if they have high labor market power, while, oppositely, large high-productivity firms have lower R&D investment rates if they possess high labor market power.

We show that our model explains this nonlinear relationship as well as several other empirical findings and can fit the actual evolution of the German economy. We then perform counterfactual simulations to find that firms' labor market power in East Germany lowered overall productivity growth by 0.2% p.a. and can explain 25% of the persistent productivity gap between East and West Germany.

While we focus on the German case, additional evidence from the CompNet dataset shows that labor market power is negatively associated with R&D activity and labor productivity also in other regions in Europe, which suggests that our findings are potentially relevant for many other countries. Innovation activity plays a critical role in determining the long-term growth of productivity and the economy in general. Our finding that labor market power is associated with lower innovation activity highlights an important new dimension through which labor market frictions can lead to aggregate welfare losses – not only statically, but dynamically and persistently.

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Appendix

A Data

A.1 Overview on variables and summary statistics

Table A1: Variable definition in the German microdata.

Variable	Definition
L_{it}	Labor in headcounts.
W_{it}	Firm wage (firm average), gross salary before taxes (including mandatory social costs) + other social expenses (including expenditures for company outings, advanced training, and similar costs) divided by the number of employees.
K_{it}	Capital derived by a perpetual inventory method following Bräuer et al. (2023), who used the same data.
M_{it}	Deflated total intermediate input expenditures, defined as expenditures for raw materials, energy, intermediate services, goods for resale, renting, temporary agency workers, repairs, and contracted work conducted by other firms. Nominal values are deflated by a 2-digit industry-level deflator supplied by the statistical office of Germany.
$P_{it}Q_{it}$	Nominal total revenue, defined as total gross output, including, among others, sales from own products, sales from intermediate goods, revenue from offered services, and revenue from commissions/brokerage.
Q_{it}	Quasi-quantity measure of physical output, i.e., $P_{it}Q_{it}$ deflated by a firm-specific price index (denoted by PI_{it}, see the definition of PI_{it} in Appendix C).
PI_{it}	Firm-specific Törnqvist price index, derived as in Eslava et al. (2004). See the Appendix C for its construction.
P_{iot}	Price of a product o.
$share_{iot}$	Revenue share of a product o in total firm revenue.
ms_{it}	Weighted average of firms product market shares in terms of revenues. The weights are the sales of each product in firms total product market sales.
G_{it}	Headquarter location of the firm (state). 90% of firms in our sample are single-plant firms.
D_{it}	A four-digit industry indicator variable. The industry of each firm is defined as the industry in which the firm generates most of its sales.
E_{it} (e_{it} in logs)	Deflated expenditures for raw materials and energy inputs. Nominal values are deflated by a 2-digit industry-level deflator for intermediate inputs and which is supplied by the federal statistical office of Germany. E_{it} is part of M_{it}.
Exp_{it}	Dummy-variable being one, if firms generate export market sales.
$NumP_{it}$	The number of products a firm produces.
$R\&Dintensity_{it}$	R&D expenditures divided by total sales revenue.
$Profits_{it}$	Total sales revenue minus total labor costs, capital costs (calculated with interest rate of 8%) and intermediate input costs.

Table A2: Descriptives for East and West Germany, 1999-2016, source: AFiD

	Number of employees	DHS employment growth rate	Nom. R&D expenditures	Log TFPQ (industry demeaned)	Real wage (1995, EUR)	Markup, μ	LMP (Wage markdown), γ	Combined market power, $\mu \times \gamma$	Output elasticity of labor, θ^L	Output elasticity of capital, θ^K	Output elasticity of intermediates, θ^M	Returns to scale
West Germany												
Observations	247129	185735	205693	244298	247129	242733	242733	242733	242733	242733	242733	242733
Mean	318.961	0.003	2934262.192	0.013	35155.981	1.104	0.988	1.054	0.302	0.109	0.640	1.051
SD	2269.724	0.122	62251574.735	0.221	11204.562	0.177	0.421	0.383	0.108	0.058	0.101	0.110
p25	49.000	-0.043	0.000	-0.108	27739.136	0.981	0.680	0.781	0.229	0.071	0.570	0.976
Median	99.000	0.000	0.000	0.025	34860.255	1.070	0.909	0.995	0.303	0.102	0.638	1.045
p75	243.000	0.052	184723.000	0.149	42029.000	1.190	1.211	1.258	0.376	0.139	0.707	1.116
East Germany												
Observations	47846	34525	40360	47191	47846	47072	47072	47072	47072	47072	47072	47072
Mean	147.253	0.011	734430.693	-0.067	25544.039	1.047	1.148	1.162	0.309	0.109	0.612	1.030
SD	372.650	0.130	20335605.581	0.208	9038.362	0.181	0.480	0.433	0.112	0.055	0.106	0.098
p25	40.000	-0.041	0.000	-0.194	19422.708	0.923	0.790	0.855	0.233	0.074	0.540	0.963
Median	72.000	0.003	0.000	-0.065	24188.759	1.008	1.057	1.084	0.311	0.103	0.609	1.026
p75	144.000	0.066	41212.000	0.064	30009.050	1.128	1.423	1.386	0.387	0.136	0.682	1.092
Germany total												
Observations	294975	220260	246053	291489	294975	289805	289805	289805	289805	289805	289805	289805
Mean	291.110	0.004	2573424.489	0.000	33596.889	1.095	1.014	1.071	0.303	0.109	0.635	1.048
SD	2083.881	0.123	57516023.628	0.221	11444.843	0.179	0.435	0.393	0.109	0.058	0.103	0.109
p25	47.000	-0.043	0.000	-0.125	25501.040	0.971	0.695	0.792	0.229	0.071	0.565	0.973
Median	93.000	0.000	0.000	0.010	33161.869	1.061	0.931	1.008	0.304	0.103	0.634	1.042
p75	221.000	0.054	146236.000	0.138	40824.040	1.181	1.244	1.279	0.378	0.138	0.704	1.112

B Additional theoretical results

B.1 Deriving a labor market power expression

In the following, we detail the derivation of firms' labor market power, given that they have monopsony power. Our empirical measure of labor market power could alternatively also be micro-founded within a bargaining model where firms pay wages above the marginal revenue product due to sharing product market rents. The notation follows the main text.

Firms manufacture output with the production function $Q_{it} = Q_{it}(.) = F(L_{it}, K_{it}, M_{it})\Omega_{it}$. Firms minimize costs using the cost function $w_{it}(L_{it})L_{it} + z_{it}M_{it} + r_{it}K_{it}$. Note that wages are a function of labor quantities. The Lagrangian writes:

$$\mathcal{L} = w_{it}(L_{it})L_{it} + z_{it}M_{it} + r_{it}K_{it} - \lambda_{it}(Q_{it} - Q_{it}(.)). \tag{B1}$$

The first order condition with respect to intermediates writes:

$$z_{it} = \lambda_{it}\frac{\partial Q_{it}}{\partial M_{it}}. \tag{B2}$$

λ_{it} is the shadow value of producing one more unit of output and therefore equals marginal costs: $\lambda_{it} = MC_{it} = \frac{P_{it}}{\mu_{it}}$. The first order condition with respect to labor is:

$$w_{it}\left(1 + \frac{\partial w_{it}}{\partial L_{it}}\frac{L_{it}}{w_{it}}\right) = \lambda_{it}\frac{\partial Q_{it}}{\partial L_{it}} = MRPL_{it}. \tag{B3}$$

$\frac{\partial w_{it}}{\partial L_{it}}\frac{L_{it}}{w_{it}} = \frac{1}{\epsilon^L_{it}}$ is the inverse labor supply elasticity. Expanding Equation (B3) with $\frac{L_{it}}{Q_{it}}\frac{Q_{it}}{L_{it}}$ and inserting Equation (B2) yields the wage markdown expression from the main text:

$$\gamma_{it} = \left(1 + \frac{\partial w_{it}}{\partial L_{it}}\frac{L_{it}}{w_{it}}\right) = \frac{\theta^L_{it}}{\theta^M_{it}}\frac{z_{it}M_{it}}{w_{it}L_{it}}, \tag{B4}$$

where γ_{it} is the wage markdown, i.e., the wedge between the wage and the marginal revenue product of labor that is shaped by the labor supply elasticity.

C Production function and productivity estimation

Production function specification. As discussed in the main text, we rely on a translog production function:

$$q_{it} = \boldsymbol{\phi}'_{it}\,\boldsymbol{\beta} + \omega_{it} + \epsilon_{it}\,, \tag{C1}$$

where $\boldsymbol{\phi}'_{it}$ captures the production inputs capital (K_{it}), labor (L_{it}), and intermediates (M_{it}) and its interactions:

$$\begin{aligned} q_{it} =& \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} + \beta_{ll} l_{it}^2 + \beta_{mm} m_{it}^2 + \beta_{kk} k_{it}^2 + \\ & \beta_{lk} l_{it} k_{it} + \beta_{lm} l_{it} m_{it} + \beta_{km} k_{it} m_{it} + \beta_{lkm} l_{it} k_{it} m_{it} + \omega_{it} + \epsilon_{it}, \end{aligned} \tag{C2}$$

where smaller letter denote logs. ϵ_{it} is an i.i.d. error term and ω_{it} denotes Hicks-neutral productivity and follows a Markov process. ω_{it} is unobserved in the data, yet firms' know ω_{it} before making input decisions for flexible inputs (intermediate inputs). We assume that only firms input decision for intermediates depends on productivity shocks. Labor and capital do not respond to contemporary productivity shocks.[11] The output elasticity of labor (and analogously for any other input) is:

$$\frac{\partial q_{it}}{\partial l_{it}} = \beta_l + 2\beta_{ll} l_{it} + \beta_{lm} m_{it} + \beta_{lk} k_{it} + \beta_{lkm} k_{it} m_{it}\,.$$

There are three identification issues preventing us from estimating the production function by OLS.

1. Firstly, we need to estimate a physical production model to recover the relevant output elasticities. Although we observe product quantities, quantities cannot be aggregated across the products of multi-product firms. Relying on the standard practice to use industry-specific output deflators does not solve this issue if output prices vary within industries.

2. Secondly, firm-specific input prices for capital and intermediate inputs are also unobserved. If input prices are correlated with input decisions and output levels, an endogeneity issue arises.

3. Thirdly, as firms flexible input decisions depend on unobserved productivity shocks, we face another endogeneity problem. We now discuss how we solve these three identification problems.

Solving (1) by deriving a firm-specific output price index. As aggregating output quantities (measured in different units) across a firm's product portfolio is not meaningful, we follow Eslava et al. (2004) and construct a firm-specific price index from observed output

[11] The timing assumption on labor is consistent with Germany's rigid labor market and with the timing of the data collection. Whereas the labor information pertains to a fixed date (September 30$^{\text{th}}$), all other variables refer to the entire year.

prices. We use this price index to deflate observed firm revenue.[12] We construct firm-specific Törnqvist price indices for each firms composite revenue from its various products in the following way:

$$PI_{it} = \prod_{o=1}^{n} \frac{p_{iot}}{p_{iot-1}}^{1/2(share_{iot}+share_{iot-1})} PI_{it-1} \,. \tag{C3}$$

PI_{it} is the price index, p_{iot} is the price of good o, and $share_{iot}$ is the share of this good in total product market sales of firm i in period t. The growth of the index value is the product of the individual products price growths, weighted with the average sales share of that product in t and $t-1$. The first year available in the data is the base year ($PI_{i1995} = 100$). If firms enter after 1995, we follow Eslava et al. (2004) and use an industry average of the computed firm price indices as a starting value. Similarly, we impute missing product price growth information in other cases with an average of product price changes within the same industry.[13] After deflating firm revenue with this price index, we end up with a quasi-quantity measure of output, for which, with slightly abusing notation, we keep using q_{it}.[14]

Solving (2) by accounting for unobserved input price variation. To account for input price variation across firms, we use a firm-level adaptation of the approach in De Loecker et al. (2016) and define a price-control function from firm-product-level output price information that we add to the production function (Eq. (C1)):

$$q_{it} = \tilde{\boldsymbol{\phi}}'_{it}\boldsymbol{\beta} + B((pi_{it}, ms_{it}, G_{it}, D_{it}) \times \tilde{\boldsymbol{\phi}}^c_{it}) + \omega_{it} + \epsilon_{it} \,. \tag{C4}$$

$B(.) = B((pi_{it}, ms_{it}, G_{it}, D_{it}) \times \tilde{\boldsymbol{\phi}}^c_{it})$ is the price control function consisting of our logged firm-specific output price index (pi_{it}), a logged sales-weighted average of firms product market sales shares (ms_{it}), a headquarter location dummy (G_{it}), and a four-digit industry dummy (D_{it}). $\tilde{\boldsymbol{\phi}}^c_{it} = [1; \tilde{\boldsymbol{\phi}}_{it}]$, where $\tilde{\boldsymbol{\phi}}_{it}$ includes the production function input terms. The tilde indicates that some of these inputs enter in monetary terms and are deflated by an industry-level deflator (capital and intermediates), while other inputs enter in quantities (labor). The constant entering $\tilde{\boldsymbol{\phi}}^c_{it}$ highlights that elements of $B(.)$ enter the price control function linearly and interacted with $\tilde{\boldsymbol{\phi}}_{it}$ (a consequence of the translog specification). The idea behind the price-control function, $B(.)$, is that output prices, product market shares, firm location, and firms industry affiliation are informative about firms' input prices. In particular, we assume that product prices and market shares contain information about product quality and that producing high-quality products requires expensive, high-quality inputs. As De Loecker et al. (2016) discuss, this motivates adding a control function containing output price and market

[12]This approach has also been applied in other studies (e.g., Smeets and Warzynski (2013), Carlsson et al. (2021).)

[13]For roughly 30% of all product observations in the data, firms do not report quantities as the statistical office views them as not being meaningful.

[14]As discussed in Bond et al. (2021), using an output price index does not fully purge firm-specific price variation. There remains a base year price difference. Yet, using a firm-specific price index follows the usual practice of using price indices to deflate nominal values. We are thus following the best practice. Alternative approaches that deal with multi-product firms require other strong assumptions like perfect input divisibility of all inputs across all products. Finally, our results are also robust to using cost-share approaches to estimate the production function, which requires other assumptions.

share information to the right-hand side of the production function to control for unobserved input price variation emerging from input quality differences across firms. We also include location and four-digit industry dummies into $B(.)$ to absorb the remaining differences in local and four-digit industry-specific input prices. Conditional on elements in $B(.)$, we assume that there are no remaining input price differences across firms. Although restrictive, this assumption is more general than the ones employed in most other studies, which implicitly assume that firms face identical input and output prices within industries.

A difference between the original approach of De Loecker et al. (2016) and our version is that they estimate product-level production functions. We transfer their framework to the firm level using firm-product-specific sales shares in firms total product sales to aggregate firm-product-level information to the firm level. This implicitly assumes that (i) firm aggregates of product quality increase in firm aggregates of product prices and input quality, (ii) firms' input costs for inputs entering as deflated expenditures increase in firms' input quality, and (iii) product price elasticities are equal across the firms' products. These or even stricter assumptions are always implicitly invoked when estimating firm-level production functions. Finally, note that even if some of the above assumptions do not hold, including the price control function is still the best practice. This is because the price control function can nevertheless absorb some of the unobserved price variation and does not require that input prices vary between firms with respect to all elements of $B(.)$. The estimation can regularly result in coefficients implying that there is no price variation at all. The attractiveness of a price control function lies in its agnostic view about the existence and degree of input price variation.

Solving (3) by controlling for unobserved productivity. To address the dependence of firms intermediate input decision on unobserved productivity, we employ a control function approach following Olley and Pakes (1996) and subsequent work. We base our control function on firms energy consumption and raw materials (e_{it}), which are part of intermediate inputs. Inverting the demand function for e_{it} defines an expression for productivity:

$$\omega_{it} \equiv g(.) = g(e_{it}, k_{it}, l_{it}, \mathbf{\Gamma}_{it}). \tag{C5}$$

$\mathbf{\Gamma}_{it}$ captures state variables of the firm that, in addition to k_{it} and l_{it}, affect firms' demand for e_{it}. Ideally, $\mathbf{\Gamma}_{it}$ should include a wide set of variables affecting productivity and demand for e_{it}. We include a dumm variables for export (EX_{it})) activities, the log of a firm's number of products ($NumP_{it}$), and the log of its average wage (w_{it}) into $\mathbf{\Gamma}_{it}$. The latter absorbs unobserved quality and price differences that shift input demand for e_{it}.

Remember that productivity follows a first-order Markov process. We allow firms to shift this Markov process as described in De Loecker (2013): $\omega_{it} = h(\omega it-1, \mathbf{Z}_{it-1}) + \xi_{it}^{tfp} = f(.) + \xi_{it}^{tfp}$, where ξ_{it}^{tfp} denotes the innovation in productivity and $\mathbf{Z}_{it} = (EX_{it}, NumP_{it})$ reflects that we allow for learning effects from export market participation and (dis)economies of scope through adding and dropping products to influence firm productivity.Plugging Eq. (C5) and the law of motion for productivity into Eq. (C4) yields:

$$q_{it} = \tilde{\boldsymbol{\phi}}'_{it}\boldsymbol{\beta} + B(.) + f(.) + \epsilon_{it} + \xi^{tfp}_{it} \,. \tag{C6}$$

Identifying moments and results We estimate Eq. (C6) separately by two-digit NACE rev. 1.1 industries using a one-step estimator as in Wooldridge (2009).[15] Our estimator uses lagged values of flexible inputs (i.e., intermediates) as instruments for their contemporary values to address the dependence of firms flexible input decisions on realizations of ξ^{tfp}_{it}. Similarly, we use lagged values of terms including firms market share and output price index as instruments for their contemporary values.[16] Our identifying moments are:

$$E[(\epsilon_{it} + \xi^{tfp}_{it})\mathbf{O}_{it}] = 0, \tag{C7}$$

where $\mathbf{O}_{it}$ includes lagged interactions of intermediate inputs with labor and capital, contemporary interactions of labor and capital, contemporary location and industry dummies, the lagged output price index, lagged market shares, lagged elements of $h(.)$, and lagged interactions of the output price index with production inputs. Formally, this implies:

$$\mathbf{O}'_{it} = (\boldsymbol{J(.)}, \boldsymbol{A(.)}, \boldsymbol{\Theta}(.), \boldsymbol{\Psi}(.),) \,, \tag{C8}$$

where for convenience, we defined:

$$\boldsymbol{J(.)} = (Exp_{it-1},\ NumP_{it-1},\ w_{it-1}, l_{it},\ k_{it},\ l^2_{it},\ k^2_{it},\ l_{it}k_{it},\ G_{it},\ D_{it}) \,,$$

$$\boldsymbol{A(.)} = (m_{it-1},\ m^2_{it-1},\ l_{it-1}m_{it-1},\ k_{it-1}m_{it-1},\ l_{it-1}k_{it-1}m_{it-1},\ ms_{it-1},\ \pi_{it-1}) \,,$$

$$\boldsymbol{\Theta}(.) = \big((l_{it-1},\ k_{it-1},\ l^2_{it-1},\ k^2_{it-1},\ l_{it-1}k_{it-1},\ m_{it-1},\ m^2_{it-1},\ l_{it-1}m_{it-1},\ k_{it-1}m_{it-1},\ l_{it-1}k_{it-1}m_{it-1}) \times \pi_{it-1}\big),$$

$$\boldsymbol{\Psi}(.) = \textstyle\sum_{n=0}^{3} \sum_{w=0}^{3-b} \sum_{h=0}^{3-n-b}\ l^n_{it-1}\, k^b_{it-1}\, e^h_{it-1} \,.$$

We drop observations with negative output elasticities from the data as these are inconsistent with our production model. Overall, average output elasicities for capital, intermediate inputs, and labor equal 0.11, 0.64, and 0.30, respectively. Average returns to scale are 1.05.

[15] We approximate $f(.)$ by a third-order polynomial in all of its elements, except for the variables in $\boldsymbol{\Gamma}_{it}$. Those we add linearly. $B(.)$ is approximated by a flexible polynomial where we interact the output price index with elements in $\tilde{\boldsymbol{\phi}}_{it}$ and add the vector of market shares, the output price index, and the location and industry dummies linearly. Interacting further elements of $B(.)$ with $\tilde{\boldsymbol{\phi}}_{it}$ creates too many parameters to be estimated. This implementation is similar to De Loecker et al. (2016).

[16] This also addresses simultaneity concerns with respect to the price variables entering our estimation.

D Estimation of labor supply elasticity

As described in Section 3.2 our measure for labor market power obtained through the production approach, is a general measure for firm-level markdowns and measures the average labor market power over a firm's workers. In our empirical analysis we view its general applicability, irrespective of the specific source of labor market power, as an asset, as we can measure it without assuming a specific type of LMP. However in our model, we employ a specific form of LMP, which is a monopsonistic labor market characterized by upward sloping firm-level labor supply functions. This is in line with many, but not all potential causes of LMP. An upward sloping labor supply function could apply to firms that operate in labor markets with low mobility, in regionally fractured labor markets or worker preferences. Our theoretical model in Section 4 therefore introduces LMP through monopsonistic wage-setting behaviour by the firm, which therefore has labor market power over a given pool of workers. To connect this model choice to our empirical results on wage markdowns, we employ a second estimation technique to directly estimate the labor supply elasticity. Since average markdowns across our German manufacturing sample are estimated close to 1, we do not expect to find that the wage elasticity is generally high in Germany. But we do expect to find significant differences in LMP between East and West Germany. To estimate the elasticity of labor with respect to wages, we need exogenous variation in the demand for labor that is isolated from firm level wages as the co-relationship between wages and labor is typically determined by common shocks. We employ an IV approach from the literature to obtain such exogenous labor demand shocks by exploiting export shocks, stemming from changing import demand in China. In this, we follow closely the analysis in Bräuer et al. (2023) and utilize the country selection from Dauth et al. (2014) to determine the magnitude of the export shocks from several different countries. We follow Bräuer et al. (2023) in arguing that the exporting behavior of these countries is exogenous from the perspective of German manufacturing firms. We calculate these exogenous export shocks at the product level and link the shocks to product information in our data. We observe at the firm level, which products firms have and the shares in revenues stemming from these products. We use this information to aggregate the product level demand shocks to the firm level. Our sample is therefore limited to firms where we observe the product mix with adequate coverage, lowering our sample size. The firms covered are both exporting and non-exporting firms, but we argue that export demand affects not only exporting firms, but also their competitors, business partners and suppliers on the domestic market by increasing aggregate demand for a specific product. The firm-level demand shocks are then used as an instrument for labor demand at the firm level. Since we do not observe individual workers, we can only use average wages at the firm level, in line with our previous analysis on wage markdowns. Table D1 shows the result of the instrumental variables estimation. Panel A shows that the first stage of the IV regression is strongly significant and thus a relevant instrument for labor demand. Column (1), Panel B shows that overall the labor supply elasticity, i.e. the coefficient of regressing log. wages on log. labor, is positive, but close to 0 and insignificant in Germany. This is in line with our average LMP measure being close to 1 across the entire country in Table A2. When we look at differences between East and West however, Column (2) shows that there are significant differences in the labor supply elasticities across the two regions. The coefficient of the interaction term showing this difference is in fact close to the wage markdown (LMP) difference that we observe between East and West Germany in Table A2. This leads us to believe that our LMP measure reflects systematic differences in labor market power exerted by firms and that this is in line with monopsonistic competition on the labor market. Furthermore this result corroborates our empirical findings further as the differences in LMP across East and West Germany are confirmed also for this specific channel of LMP.

Panel A: First stage - Export shock relevance		
	(1)	(2)
	ln(L)	ln(L)
Export shock	0.0162***	0.0135***
	(0.000720)	(0.000764)
Inter: Export shock x East		0.0170***
		(0.00161)
Constant	4.598***	4.639***
	(0.0103)	(0.0110)
Panel B: Second stage IV regression		
	(1)	(2)
	ln(wage)	ln(wage)
ln(L)	0.0384	0.0149
	(0.0418)	(0.0465)
Inter: ln(L) x East		0.142**
		(0.0555)
Constant	10.14***	10.26***
	(0.201)	(0.226)
Observations	148,988	148,988
Number of unr	25,864	25,864
R-squared	0.044	0.045
Year FE	Yes	Yes
Firm FE	Yes	Yes

Table D1: IV regression: Estimating labor supply elasticity from exogenous demand shocks

Notes: IV regression using export shocks defined as in Dauth et al. 2013 to estimate average firm-level labor supply curve elasticities by utilizing the export shocks as exogenous demand shifters. The regression features firm FE and time FE. The sample is limited to firms, for which we have full coverage of associated products, product shares in revenue and therefore can aggregate the product-level export shock to the firm-level. *Source*: AFiD, own calculations

E Robustness checks

Table E1: Correlation of R&D intensity and LMP: FTE version; source: AFiD, own calculations

VARIABLES	(1) R&D/sales	(2) R&D/sales	(3) R&D/sales	(4) R&D/sales	(5) R&D/sales
Labor market power		-0.00743***	-0.00629***	-0.00851***	-0.00766***
		(0.000481)	(0.000448)	(0.000516)	(0.000550)
East = 1				0.00364***	0.00384***
				(0.000425)	(0.000431)
East = 1 # LMP_base					-0.00348***
					(0.000744)
l	0.00267***	0.00288***	0.00119***	0.00321***	0.00310***
	(0.000237)	(0.000238)	(0.000369)	(0.000241)	(0.000242)
k	0.00211***	0.00315***	0.00194***	0.00317***	0.00318***
	(0.000157)	(0.000175)	(0.000316)	(0.000176)	(0.000175)
Constant	-0.0368***	-0.0469***	-0.0210***	-0.0482***	-0.0487***
	(0.00196)	(0.00215)	(0.00494)	(0.00216)	(0.00215)
Observations	239,446	239,446	239,446	239,446	239,446
R-squared	0.204	0.211	0.009	0.213	0.213
Industry4d FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	No	No
Firms	39162	39162	39162	39162	39162

Model: base; clustered standard errors on firm level in parentheses. Pooled OLS regression.

Table E2: Correlation of R&D intensity and LMP; source: AFiD, own calculations

VARIABLES	(1) R&D/Sales	(2) Patents per year
LMP (base)	-0.00830***	-0.480
	(0.000531)	(0.417)
East = 1	0.00438***	0.325*
	(0.000453)	(0.170)
East = 1 # LMP_base	-0.00240***	-1.157***
	(0.000786)	(0.405)
l	0.00278***	1.907***
	(0.000245)	(0.668)
k	0.00338***	0.0327
	(0.000182)	(0.0748)
Constant	-0.0497***	-8.549***
	(0.00217)	(1.917)
Observations	217,883	217,883
R-squared	0.217	0.031
Industry4d FE	Yes	Yes
Year FE	Yes	Yes
Firms	38878	38878

Model: base. Clustered standard errors on firm level in parentheses.
Pooled OLS regression.

Table E3: Alternative model specification (EW) - Correlation of R&D intensity and LMP; source: AFiD, own calculations

VARIABLES	(1) R&D/sales	(2) R&D/sales	(3) R&D/sales	(4) R&D/sales	(5) R&D/sales
Labor market power		-0.00428***	-0.00130***	-0.00462***	-0.00480***
		(0.000335)	(0.000235)	(0.000341)	(0.000396)
East = 1				0.00360***	0.00353***
				(0.000463)	(0.000470)
East = 1 # LMP_ew					0.000789
					(0.000640)
l	0.00264***	0.00259***	0.000253	0.00289***	0.00290***
	(0.000247)	(0.000247)	(0.000445)	(0.000248)	(0.000249)
k	0.00210***	0.00278***	0.00187***	0.00269***	0.00271***
	(0.000162)	(0.000177)	(0.000438)	(0.000177)	(0.000180)
Constant	-0.0369***	-0.0433***	-0.0209***	-0.0434***	-0.0435***
	(0.00198)	(0.00211)	(0.00719)	(0.00211)	(0.00213)
Observations	173,531	173,531	173,531	173,531	173,531
R-squared	0.206	0.210	0.005	0.212	0.212
Industry4d FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	No	No
Firms	35052	35052	35052	35052	35052

Model: ew; clustered standard errors on firm level in parentheses. Pooled OLS regression.

F Mathematical Appendix

F.1 Labor Market Model with Congestion Externality and Fréchet Shocks eq. (10)

We derive eq. (10) from its components

$$l_f = p(f) \cdot \bar{L} = p(f|R) \cdot \frac{p(R)}{p(c)} \cdot p(c) \cdot \bar{L}$$

Firm employment share in region R $p(f|R)$:

The probability to choose firm f given the worker is already committed to region R is given by the standard logit formula, i.e. constructed by ratios of e to the power of utility parameters. Potential utility from every firm is Gumbel distributed around the wage the firm offers, i.e. $U_f \sim \text{Gumbel}(\mu_f = ln(w_f), \beta = \varepsilon_R)$. Since this is the case, it is well known that

$$\Pr\left[j = \arg\max_{f \in R} U_f\right] = \frac{e^{\mu_f \frac{1}{\beta}}}{\int e^{\mu_{f'} \frac{1}{\beta}}\, df'} = \frac{w_f^{\frac{1}{\beta}}}{\int w_f^{\frac{1}{\beta}}\, df'} = \frac{w_f^{\frac{1}{\beta}}}{\mathbf{W}_R}$$

Employment in Region r relative to the final goods sector $\frac{p(R)}{p(c)}$:

Workers can freely choose regions, which means that the expected utility of all regions must equalize. However, workers only draw the shocks after arriving in the region/nest, so they have to form expectations about the best combination of shock and wage.

Current utility is

$$v_{i,f} = \ln w_f \;+\; \varepsilon_R(\ln \tilde{\varepsilon}_{i,f} + \ln(s_c/s_R))$$

with $\tilde{\varepsilon}_{i,f} \sim \text{Fréchet}(\alpha = 1,\, s = e^{-\gamma})$. The logarithm of a Frechet distributed variable is Gumbel distributed, so $\varepsilon_R \ln \tilde{\varepsilon} \sim \text{Gumbel}(-\gamma\varepsilon_R, \varepsilon_R) = -\gamma\varepsilon_R + \text{Gumbel}(0, \varepsilon_R)$.

Note that the taste shocks within a region all come from the same Gumbel distribution, only shifted by the wage each firm offers and terms that are constant within the nest: nest congestion $\varepsilon \ln(s_c/s_R)$ and the mean location of shocks $-\gamma\varepsilon_R$. The maximum of such a set of draws from identical-except-for-the-location Gumbel distributions is again Gumbel distributed with a known location and shape parameter (Ben-Akiva and Lerman, 1985, p. 105):

$$M_i = \max_{f=1,\ldots,N} X_{i,f} \sim \text{Gumbel}(\beta \cdot \ln\left(\int_0^N e^{\mu_{i,f}/\beta}\right), \beta),$$

where β is the common shape parameter and $\mu_{i,f}$ is the location of each individual Gumbel distribution. Inserting that in our case, $\beta = \varepsilon_R$ and $\mu_{i,f} = \ln w_f - \varepsilon_R\gamma + \varepsilon_R \ln(\frac{s_c}{s_R})$, we get

$$\begin{aligned}
M_i = \max_{i=1,\dots,N} X_i &\sim \text{Gumbel}(\varepsilon_R \cdot \ln\left(\int_0^N e^{\frac{\ln w_f - \varepsilon_R\gamma + \varepsilon_R \ln(\frac{s_c}{s_R})}{\varepsilon_R}}\right), \varepsilon_R) \\
&\sim \text{Gumbel}(\varepsilon_R \cdot \ln\left(\int_0^N e^{\frac{\ln w_f}{\varepsilon_R} + \ln(\frac{s_c}{s_R}) - \gamma}\right), \varepsilon_R) \\
&\sim \text{Gumbel}(\varepsilon_R \cdot \ln\left(e^{\ln(\frac{s_c}{s_R}) - \gamma} \int_0^N e^{\frac{\ln w_f}{\varepsilon_R}}\right), \varepsilon_R) \\
&\sim \text{Gumbel}(\varepsilon_R \cdot \ln\left(e^{\ln(\frac{s_c}{s_R}) - \gamma}\right) + \varepsilon_R \ln\left(\int_0^N e^{\frac{\ln w_f}{\varepsilon_R}}\right), \varepsilon_R) \\
&\sim \text{Gumbel}(\varepsilon_R \cdot \ln\left(e^{\ln(\frac{s_c}{s_R}) - \gamma}\right) + \varepsilon_R \ln\left(\int_0^N e^{\frac{\ln w_f}{\varepsilon_R}}\right), \varepsilon_R) \\
&\sim \text{Gumbel}(\varepsilon_R[\ln(\frac{s_c}{s_R}) - \gamma] + \varepsilon_R \ln\left(\int_0^N w_f^{\frac{1}{\varepsilon_R}}\right), \varepsilon_R)
\end{aligned}$$

The expected value of any random variable $X \sim \text{Gumbel}(a, b)$ is $E(X) = a + b\gamma$. Thus, the expected value of the best draw from nest R is

$$\begin{aligned}
E(M_i) &= \varepsilon_R[\ln(\frac{s_c}{s_R}) - \gamma] + \varepsilon_R \ln\left(\int_0^N w_f^{\frac{1}{\varepsilon_R}}\right) + \varepsilon_R\gamma \\
&= \varepsilon_R \ln(\frac{s_c}{s_R}) + \varepsilon_R \ln \mathbf{W}_R
\end{aligned}$$

Workers will move unless this expected utility is equal across regions and thus also equal to utility from the final goods sector nest, which is just $\ln(w_c)$. Thus, free movement implies that

$$\begin{aligned}
\ln(w_c) &= \varepsilon_R \ln(\frac{s_c}{s_R}) + \varepsilon_R \ln \mathbf{W}_R \\
w_c &= e^{\ln(\frac{s_c}{s_R})^{\varepsilon_R} + \ln(\mathbf{W}_\mathsf{R})^{\varepsilon_R}} \\
w_c &= e^{\ln(\frac{s_c}{s_R})^{\varepsilon_R} + \ln(\mathbf{W}_\mathsf{R})^{\varepsilon_R}} \\
w_c &= (\frac{s_c}{s_R})^{\varepsilon_R} * (\mathbf{W}_\mathsf{R})^{\varepsilon_R} \\
\frac{w_c}{(\mathbf{W}_\mathsf{R})^{\varepsilon_R}} &= (\frac{s_c}{s_R})^{\varepsilon_R} \\
\frac{w_c^{\frac{1}{\varepsilon_R}}}{\mathbf{W}_\mathsf{R}} &= \frac{s_c}{s_R} \\
\frac{\mathbf{W}_\mathsf{R}}{w_c^{\frac{1}{\varepsilon_R}}} &= \frac{p(R)}{p(c)}
\end{aligned}$$

The last step relies on the fact that since all workers are identical, the probability of a worker choosing region R is equal to the employment share of region.

Employment in the final goods sector $p(c) \cdot \bar{L}$ Again, since all workers are identical, the probability that a worker chooses c is equal to its employment share. For the same reason, $p(c) \cdot \bar{L}$ is the employment of the final goods sector, L_c.

Labor supply to firm f l_f:

Combing all of the above,

$$
\begin{aligned}
l_f = p(f) \cdot \bar{L} &= p(f|R) \cdot \frac{p(R)}{p(c)} \cdot p(c) \cdot \bar{L} \\
&= \frac{w_f^{\frac{1}{\varepsilon_R}}}{\mathbf{W}_R} \cdot \frac{\mathbf{W}_R}{w_c^{1/\varepsilon_R}} \cdot L_c \\
&= \left(\frac{w_f}{w_c}\right)^{\frac{1}{\varepsilon_R}} \cdot L_c
\end{aligned}
$$

Which is the result presented in the paper.

Monopolistic Intermediate Goods Firms

$$
\max_{l_j} \ \pi_j = \underbrace{L_c^{\beta} A_j^{\beta} \bar{A}^{1-\beta} l_j^{1-\beta}}_{\text{Revenue}} - \underbrace{w_c L_c^{-\varepsilon_R} l_j^{1+\varepsilon_R}}_{\text{Cost}} \tag{F1}
$$

$$
l_j^* = \left(\frac{(1-\beta)}{(1+\varepsilon_R)} \cdot A_j^{\beta} \bar{A}^{1-\beta} \cdot w_c^{-1} \cdot \right)^{\frac{1}{\beta+\varepsilon_R}} \cdot L_c \tag{F2}
$$

$$
l_j^* = \left[\frac{(1-\beta)}{(1+\varepsilon_R)} \cdot \left(\frac{A_j}{\bar{A}}\right)^{\beta} \left(\frac{\bar{A}}{w_c}\right) \right]^{\frac{1}{\beta+\varepsilon_R}} \cdot L_c
$$

$$
w_j^* = w_c \left(\frac{l_f^*}{L_c}\right)^{\varepsilon_R} = \left[\frac{(1-\beta)}{(1+\varepsilon_R)} \cdot \left(\frac{A_j}{\bar{A}}\right)^{\beta} \cdot \bar{A} \cdot \right]^{\frac{\varepsilon_R}{\beta+\varepsilon_R}} w_c^{\frac{\beta}{\beta+\varepsilon_R}}
$$

$$
p_j^* = L_c^{\beta} A_j^{\beta} k_j^{-\beta} = L_c^{\beta} A_j^{\beta} \left(\bar{q} l_j\right)^{-\beta} = A_j^{\frac{\beta\varepsilon_R}{\beta+\varepsilon_R}} \bar{q}^{\frac{1+\varepsilon_R}{\beta+\varepsilon_R}} w_c^{\frac{\beta}{\beta+\varepsilon_R}} \left(\frac{1+\varepsilon_R}{1-\beta}\right)^{\frac{\beta}{\beta+\varepsilon_R}}
$$

$$
\text{Revenue}_j = L_c \cdot \left(\frac{\bar{q}^{(1+\varepsilon_j)}}{w_c}\right)^{\frac{(1-\beta)}{\beta+\varepsilon}} \cdot A_j^{\frac{\beta(1+\varepsilon_j)}{\beta+\varepsilon}} \left[\frac{(1-\beta)}{(1+\varepsilon_f)}\right]^{\frac{1-\beta}{\beta+\varepsilon_f}}
$$

$$\text{Wagebill}_j = L_c \cdot \left(\frac{\bar{q}^{(1+\varepsilon_j)}}{w_c}\right)^{\frac{(1-\beta)}{\beta+\varepsilon}} \cdot A_j^{\frac{\beta(1+\varepsilon_j)}{\beta+\varepsilon}} \left[\frac{(1-\beta)}{(1+\varepsilon_f)}\right]^{\frac{1+\varepsilon_f}{\beta+\varepsilon_f}}$$

$$\pi_j = L_c \cdot \left(\frac{\bar{q}^{(1+\varepsilon_j)}}{w_c}\right)^{\frac{(1-\beta)}{\beta+\varepsilon}} \cdot A_j^{\frac{\beta(1+\varepsilon_j)}{\beta+\varepsilon}} \left[\left[\frac{(1-\beta)}{(1+\varepsilon_f)}\right]^{\frac{1-\beta}{\beta+\varepsilon_f}} - \left[\frac{(1-\beta)}{(1+\varepsilon_f)}\right]^{\frac{1+\varepsilon_f}{\beta+\varepsilon_f}}\right]$$

$$\pi_j = L_c \cdot A_j \cdot \left(\frac{\bar{A}}{A_j}\right)^{\frac{\varepsilon_R(1-\beta)}{\beta+\varepsilon_R}} \cdot \frac{1}{\beta}^{\frac{(1-\beta)}{\beta+\varepsilon_R}} \left[\left[\frac{(1-\beta)}{(1+\varepsilon_f)}\right]^{\frac{1-\beta}{\beta+\varepsilon_f}} - \left[\frac{(1-\beta)}{(1+\varepsilon_f)}\right]^{\frac{1+\varepsilon_f}{\beta+\varepsilon_f}}\right]$$

$$\text{Wage Share}_j = \frac{\text{Wagebill}_j}{\text{Revenue}_j} = \frac{1-\beta}{1+\varepsilon_R}$$

$$\text{Profit Share}_j = \frac{\pi_j}{\text{Revenue}_j} = \frac{\varepsilon_R+\beta}{1+\varepsilon_R}$$

Labor Market equilibrium

To compute the labor shares of every region R:

$$\mathbf{W}_R = \int_{j\in R} (w_j^*)^{\frac{1}{\varepsilon_R}} = \int_{j\in R} \left(\left[\frac{(1-\beta)}{(1+\varepsilon_R)} \cdot \left(\frac{A_j}{\bar{A}}\right)^{\beta} \cdot \bar{A} \cdot\right]^{\frac{\varepsilon_R}{\beta+\varepsilon_R}} w_c^{\frac{\beta}{\beta+\varepsilon_R}}\right)^{\frac{1}{\varepsilon_R}}$$
$$= \int_{j\in R} \left[\frac{(1-\beta)}{(1+\varepsilon_R)} \cdot \left(\frac{A_j}{\bar{A}}\right)^{\beta} \cdot \bar{A} \cdot\right]^{\frac{1}{\beta+\varepsilon_R}} w_c^{\frac{\beta}{\varepsilon_R(\beta+\varepsilon_R)}}$$

$$
\begin{aligned}
\frac{s_R}{s_c} = \frac{\mathbf{W}_R}{w_c^{\frac{1}{\varepsilon}}} = \frac{\int_{j\in R}(w_j^*)^{\frac{1}{\varepsilon_R}}}{w_c^{\frac{1}{\varepsilon}}} &= \\
&= \frac{\int_{j\in R}\left(\left[\frac{(1-\beta)}{(1+\varepsilon_R)}\cdot\left(\frac{A_j}{\bar{A}}\right)^{\beta}\cdot\bar{A}\cdot\right]^{\frac{\varepsilon_R}{\beta+\varepsilon_R}} w_c^{\frac{\beta}{\beta+\varepsilon_R}}\right)^{\frac{1}{\varepsilon_R}}}{w_c^{\frac{1}{\varepsilon}}} \\
&= \int_{j\in R}\left(\left[\frac{(1-\beta)}{(1+\varepsilon_R)}\cdot\left(\frac{A_j}{\bar{A}}\right)^{\beta}\cdot\bar{A}\cdot\right]^{\frac{\varepsilon_R}{\beta+\varepsilon_R}} w_c^{\frac{\beta}{\beta+\varepsilon_R}} w_c^{\frac{-\beta-\varepsilon_R}{\beta+\varepsilon_R}}\right)^{\frac{1}{\varepsilon_R}} \\
&= \int_{j\in R}\left(\left[\frac{(1-\beta)}{(1+\varepsilon_R)}\cdot\left(\frac{A_j}{\bar{A}}\right)^{\beta}\cdot\bar{A}\cdot\right]^{\frac{\varepsilon_R}{\beta+\varepsilon_R}} w_c^{\frac{-\varepsilon_R}{\beta+\varepsilon_R}}\right)^{\frac{1}{\varepsilon_R}} \\
&= \int_{j\in R}\left(\left[\frac{(1-\beta)}{(1+\varepsilon_R)}\cdot\left(\frac{A_j}{\bar{A}}\right)^{\beta}\cdot\frac{\bar{A}}{w_c}\cdot\right]^{\frac{\varepsilon_R}{\beta+\varepsilon_R}}\right)^{\frac{1}{\varepsilon_R}} \\
&= \int_{j\in R}\left[\frac{(1-\beta)}{(1+\varepsilon_R)}\cdot\left(\frac{A_j}{\bar{A}}\right)^{\beta}\cdot\frac{1}{\beta}\right]^{\frac{1}{\beta+\varepsilon_R}} \\
&= \left[\frac{(1-\beta)}{\beta(1+\varepsilon_R)}\right]^{\frac{1}{\beta+\varepsilon_R}} \int_{j\in R}\left(\frac{A_j}{\bar{A}}\right)^{\frac{\beta}{\beta+\varepsilon_R}}
\end{aligned}
$$

$$
\begin{aligned}
1 = \sum_R s_R = \sum_{R\neq c}\left[\frac{(1-\beta)}{\beta(1+\varepsilon_R)}\right]^{\frac{1}{\beta+\varepsilon_R}} \int_{j\in R}\left(\frac{A_j}{\bar{A}}\right)^{\frac{\beta}{\beta+\varepsilon_R}} s_c + s_c \\
\frac{1}{s_c} = 1 + \sum_{R\neq c}\left[\frac{(1-\beta)}{\beta(1+\varepsilon_R)}\right]^{\frac{1}{\beta+\varepsilon_R}} \int_{j\in R}\left(\frac{A_j}{\bar{A}}\right)^{\frac{\beta}{\beta+\varepsilon_R}} \\
s_c = \frac{1}{1+\sum_{R\neq c}\left[\frac{(1-\beta)}{\beta(1+\varepsilon_R)}\right]^{\frac{1}{\beta+\varepsilon_R}} \int_{j\in R}\left(\frac{A_j}{\bar{A}}\right)^{\frac{\beta}{\beta+\varepsilon_R}}}
\end{aligned}
$$

$$1=\sum_R s_R=\sum_{R\neq c}\left[\frac{(1-\beta)}{\beta(1+\varepsilon_R)}\right]^{\frac{1}{\beta+\varepsilon_R}}\int_{j\in R}\left(\frac{A_j}{\bar{A}}\right)^{\frac{\beta}{\beta+\varepsilon_R}}s_c+s_c$$
$$\frac{1}{s_c}=1+\sum_{R\neq c}\left[\frac{(1-\beta)}{\beta(1+\varepsilon_R)}\right]^{\frac{1}{\beta+\varepsilon_R}}\int_{j\in R}\left(\frac{A_j}{\bar{A}}\right)^{\frac{\beta}{\beta+\varepsilon_R}}$$
$$s_c=\frac{1}{1+\sum_{R\neq c}\left[\frac{(1-\beta)}{\beta(1+\varepsilon_R)}\right]^{\frac{1}{\beta+\varepsilon_R}}\int_{j\in R}\left(\frac{A_j}{\bar{A}}\right)^{\frac{\beta}{\beta+\varepsilon_R}}}$$

$$s_R^*=\left[\frac{(1-\beta)}{\beta(1+\varepsilon_R)}\right]^{\frac{1}{\beta+\varepsilon_R}}\int_{j\in R}\left(\frac{A_j}{\bar{A}}\right)^{\frac{\beta}{\beta+\varepsilon_R}}\cdot s_c$$
$$=\frac{\left[\frac{(1-\beta)}{\beta(1+\varepsilon_R)}\right]^{\frac{1}{\beta+\varepsilon_R}}\int_{j\in R}\left(\frac{A_j}{\bar{A}}\right)^{\frac{\beta}{\beta+\varepsilon_R}}}{1+\sum_{R'\neq c}\left[\frac{(1-\beta)}{\beta(1+\varepsilon_{R'})}\right]^{\frac{1}{\beta+\varepsilon_{R'}}}\int_{j\in R'}\left(\frac{A_j}{\bar{A}}\right)^{\frac{\beta}{\beta+\varepsilon_{R'}}}}$$

Dynamic Optimization

In the main text, it is claimed that the value function of a firm in a no-labor market power region and with a linear R&D function is also linear. In that case, the expenditure function for innovation becomes

$$R(z_j,\bar{A})=\hat{\chi}*z_j^{\hat{\psi}}A_j \tag{F3}$$

i,.e research expenditures are linearly rising in the current firm productivity A_j.

Eq. (F7) becomes:

$$r*V(A_j)=\pi^* * A_j-\hat{\chi}*z_j^{\hat{\psi}}A_j-\delta(\varepsilon_R)V(A_j)+z_j[\lambda*\kappa*A_j] \tag{F4}$$

To see that the claim holds, use guess and verify: We guess that the value function is $V(A_j)=\Xi+\kappa*A_j$. Optimizing eq. (F4) with respect to the rate of innovation z_j^* gives:

$$\hat{\psi}z_j^{\hat{\psi}-1}A_j=\lambda\kappa A_j \tag{F5}$$
$$z_j^*=[\frac{\lambda*\kappa}{\hat{\chi}*\psi}]^{\frac{1}{\hat{\psi}-1}}. \tag{F6}$$

Thus, firms aim for the same arrival rate on product innovation, irrespective of productivity/quality A_j. Inserting eq. (F5) into eq. (F3), R&D expenditures rise linearly in A_j. We can insert this back into the value function:

$$(r+\delta(\varepsilon))\cdot V(A_j) = \pi^*\cdot A_j - \hat{\chi} * ([\frac{\lambda*\kappa}{\hat{\chi}*\psi}]^{\frac{1}{\hat{\psi}-1}})^{\hat{\psi}} A_j + ([\frac{\lambda*\kappa}{\hat{\chi}*\psi}]^{\frac{1}{\hat{\psi}-1}})[\lambda\kappa A_j] \tag{F7}$$

$$V(A_j) = \frac{\pi^*}{r} * A_j + [\frac{\lambda^{\hat{\psi}} * \frac{\pi^*}{r}^{\hat{\psi}}}{\hat{\chi}\hat{\psi}}]^{\frac{1}{\hat{\psi}-1}}[1-\frac{1}{\hat{\psi}}]\frac{1}{r}\bar{A} \tag{F8}$$

$$V(A_j) = \underbrace{[\frac{\pi^*}{r} + [\frac{\lambda^{\hat{\psi}} * \frac{\pi^*}{r}^{\hat{\psi}}}{\hat{\chi}\hat{\psi}}]^{\frac{1}{\hat{\psi}-1}}[1-\frac{1}{\hat{\psi}}]\frac{1}{r}}_{\Xi} * \bar{A} \tag{F9}$$

(F10)

However, this requires labor market power ε to be 0. To transfer the analytical solution to the case with labor market power, we use the finite size of each firm's labor market pool: Recall that if a firm grows above S_j, it pays the national wage. It has outgrown its local labor market and thus can no longer use its price setting power in that market. At that point, it effectively becomes a firm without labor market power $V(A_j,\varepsilon) = V(A_j,0) \iff l \geq S_j$. We can use this implication of the labor market setup for backward induction.

Specifically, there is some A_j^S such that $l \geq S_j$. For any value of A_j such that $A_j + \lambda\bar{A} \geq A_j^S$ (i.e., any quality where one additional innovation would push it above A_j^S), we can formulate the value function as:

$$r * V(A_j,\varepsilon,\bar{A}) - \dot{V}(A_j,\varepsilon,\bar{A}) =$$

$$max_{z_j}(\pi^* * A_j^{\frac{\beta(1+\varepsilon)}{\varepsilon+\beta}} - R(z_j,\bar{A}) + z_j[\kappa(A_j+\lambda\bar{A}) + \Xi\bar{A} - V(A_j,\varepsilon,\bar{A})]). \tag{F11}$$

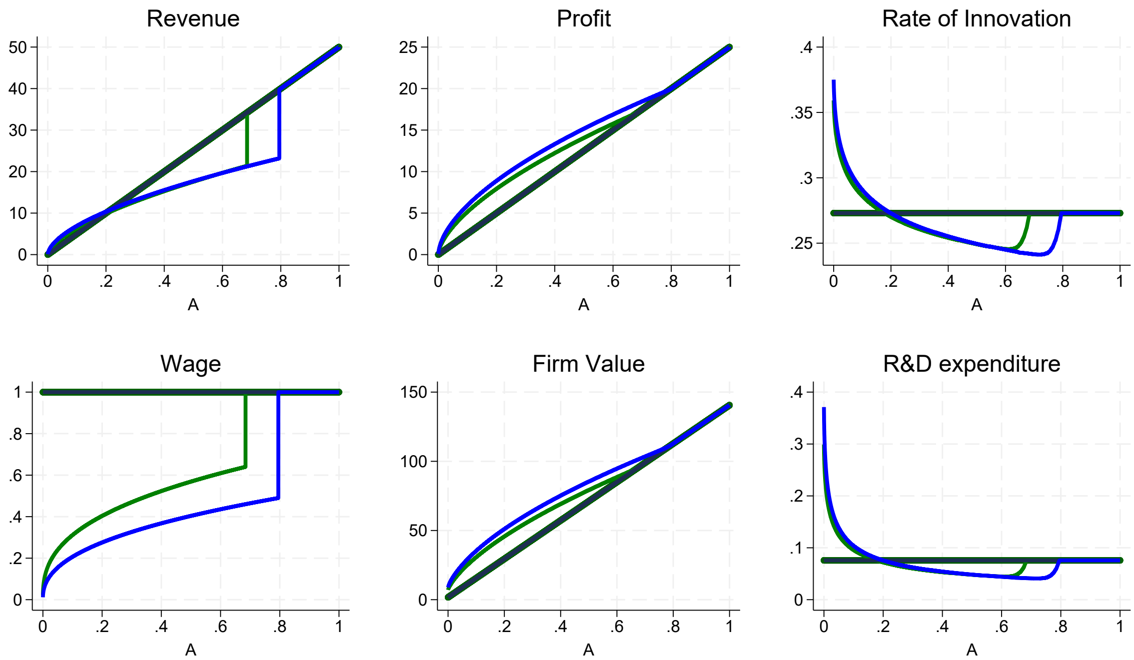
As the value of a firm in a competitive market $\kappa(A_j+\lambda\bar{A}) + \Xi\bar{A}$ is known, the equation has two unknowns (optimal z_j and the firm's value. The first derivative w.r.t. z_j yields the second equation that allows for an analytical solution to this problem. However, while the solution is analytical, it is still iterative in the sense that it goes backward innovation by innovation. Figure F1 reports firms' strategies and evaluation for different levels of ε.

Extension: Entry as a Final Goods Sectors Discrete Choice Problem

Upon Entry, an entrant and an incumbent can produce the same variety j. Consider the case where the incumbent has higher labor market power than the entrant (in all other cases, the entrant 'wins' the competition trivially). Since there is no capital market for incumbent firms, firms without revenue cannot continue to exist and invest into R&D in an effort to catch up to the leader again.

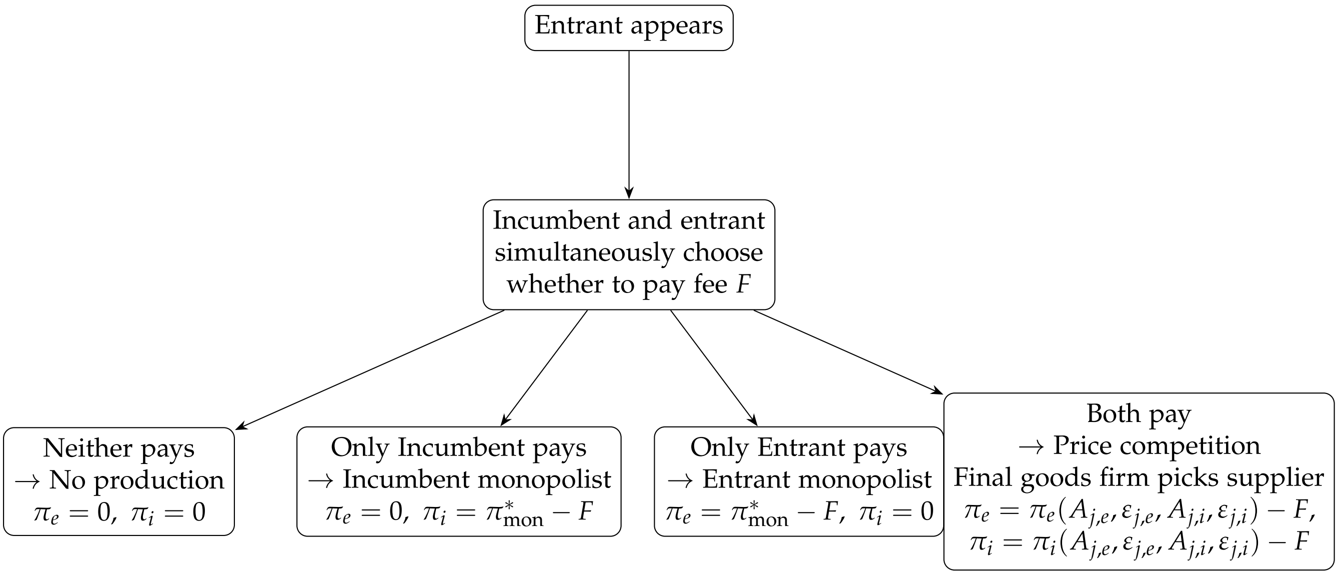
The game is described in Figure F2. Backwards induction leads to the outcome of outcome of price competition as the decisive factor for the equilibrium, i.e. what happens if both firms try to produce? Intuitively, Bertrand competition is winner-takes-all, so whoever looses the competition will get $0-F$. This will cause them to not pay the production fee ex ante if they foresee to lose.

Figure F1: Firms' optimal strategies and value functions



Notes: Key variables for firms with no labor market power, firms with $\varepsilon = 0.5$ and firms with $\varepsilon = 1.5$. There is a discrete jump in strategy when firms with labor market power become so productive that growing becomes more lucrative than exploiting ' their' labor market. Innovation is higher for small firms with labor market power, but lower for the majority of values of A.
Sources: Own simulation

Figure F2: Tree representation of the strategic interaction of entrant and incumbent



In the competition scenario, the atomistic firms of the final goods sector have to choose between competing offers. The intermediate goods represent production technologies, so it is not possible to mix them by assumption.

Firms in the final goods sector maximize profit by choosing the optimal quantity k_j, given its price and quality. We rearrange inverse demand equation 12 and insert it into the final goods profits. Note that final goods sector profit is an integral over the profits made with each variety. Thus, the decision between suppliers $f \in \{e, i\}$ for variety j is thus independent of all other varieties. Mathematically:

$$\max_{f\in\{e,i\}} \pi_{fg} = \max_{f\in\{e,i\}} L_c^\beta \left(\frac{1}{1-\beta}\right) \int_0^1 A_j^\beta k_j^{1-\beta}\, dj - \int_0^1 p_j \cdot k_j\, dj - L_c w_c \tag{F12}$$

$$= \max_{f\in\{e,i\}} L_c^\beta \left(\frac{1}{1-\beta}\right) \int_0^1 A_j^\beta \left(\frac{L_c^\beta A_j^\beta}{p_j}\right)^{\frac{1-\beta}{\beta}} dj - \int_0^1 p_j \cdot \left(\frac{L_c^\beta A_j^\beta}{p_j}\right)^{1/\beta} dj - L_c w_c \tag{F13}$$

$$= \max_{f\in\{e,i\}} \left(\frac{1}{1-\beta}\right) L_c \int_0^1 A_j \cdot p_j^{-\frac{1-\beta}{\beta}}\, dj - L_c \int_0^1 A_j \cdot p_j^{-\frac{1-\beta}{\beta}}\, dj - L_c w_c \tag{F14}$$

$$= \max_{f\in\{e,i\}} L_c A_j \left(\frac{1}{1-\beta} \cdot p_j^{-\frac{1-\beta}{\beta}}\, dj - p_j^{-\frac{1-\beta}{\beta}}\right) - L_c w_c \tag{F15}$$

$$= \max_{f\in\{e,i\}} L_c A_f \frac{\beta}{1-\beta} \cdot p_f^{-\frac{1-\beta}{\beta}} \tag{F16}$$

$$\tag{F17}$$

The firms in the final goods sector will pick the new entrant, if

$\frac{A_e}{p_e^{\frac{1-\beta}{\beta}}} \geq \frac{A_i}{p_i^{\frac{1-\beta}{\beta}}}$
$\frac{A_e}{A_i} \geq (\frac{p_e}{p_i})^{\frac{1-\beta}{\beta}}$

The final goods firms will prefer the offer with the higher quality adjusted price. Equivalently, The ratio of the qualities must be higher than the weighted ratio of the prices for the finqal goods sector to pick the entrant. So far, this is exactly as in (Akcigit and Kerr, 2018) and without labor market power, the entrant will be able to offer higher quality fot the same price (since marginal costs are then identical) and always supplant the incumbent. However, with labor market power, not all firms have the same (linear) costs and thus it is less clear that the new entrant will always win.

From the viewpoint of the intermediate firm, its profit is:

$$\pi = \begin{cases} -F & \text{if it is not chosen (all (identical) final goods firms make the same decision)} \\ \pi(A_{j,f}, p_{j,f}) - F & \text{if it is chosen} \end{cases}$$

Clearly, there can be no equilibrium where a firm can offer a price that still makes a profit, but is also not the chosen producer. Hence, both firms will engage in a price race to the bottom until one firm arrives at zero profits and can no longer profitably underbid the other firm. The equilibrium producer is thus determined by who can offer the lower quality adjusted price while still making profits.

The zero profit condition is given by equating revenue with labor costs. We then insert the linear production technology and the inverse demand function eq. (12).

$$p_{j,f} \cdot k_{j,f} = l_{j,f} \cdot w(l_{j,f}) \tag{F18}$$

$$p_{j,f} \cdot k_{j,f} = w_c \cdot (\frac{l_f}{L_c})^{\varepsilon_R} \cdot l_f \tag{F19}$$

$$p_{j,f} \cdot k_{j,f} = w_c \cdot L_c^{-\varepsilon_R} \cdot (\frac{k_j}{\bar{q}})^{1+\varepsilon_f} \tag{F20}$$

$$p_{j,f} = \frac{w_c}{\bar{A}} \cdot (\frac{A_f}{\bar{A}})^{\varepsilon_R} p^{-\frac{\varepsilon_R}{\beta}} \tag{F21}$$

$$p_{j,f}^{\frac{\varepsilon_R+\beta}{\beta}} = \frac{w_c}{\bar{A}} \cdot (\frac{A_f}{\bar{A}})^{\varepsilon_R} \tag{F22}$$

$$p_{j,f}^{\pi_f=0} = \left[\beta \cdot (\frac{A_f}{\bar{A}})^{\varepsilon_R}\right]^{\frac{\beta}{\varepsilon_R+\beta}} \tag{F23}$$

$$\tag{F24}$$

Note that if $\varepsilon = 0$, this collapses to the(Akcigit and Kerr, 2018) case and $p_{j,f}^{\pi=0} = \frac{w_c}{\bar{q}}$.

Inserting this lowest possible price into (F12) yields the cutoff condition for the entrant replacing the incumbent.

The entrant will replace the incumbent if he can offer a higher net production with his zero profit price then the incumbent:

$$\pi^{j}_{fg}(p^{\pi=0}_{j,e}, A_{j,e}) \geq \pi^{j}_{fg}(p^{\pi=0}_{j,i}, A_{j,i}) \tag{F25}$$

$$\tag{F26}$$

$$\pi_{fg,i} = \frac{\beta}{1-\beta} \cdot LA_i \cdot (p^{\pi=0}_{j,i})^{-\frac{1-\beta}{\beta}}$$

$$A_e \cdot (p^{\pi=0}_{j,e})^{-\frac{1-\beta}{\beta}} > A_i \cdot (p^{\pi=0}_{j,i})^{-\frac{1-\beta}{\beta}}$$

$$\frac{A_e}{A_i} > \left(\frac{p^{\pi=0}_{j,e}}{p^{\pi=0}_{j,i}}\right)^{\frac{1-\beta}{\beta}}$$

$$\frac{A_e}{(p^{\pi=0}_{j,e})^{\frac{1-\beta}{\beta}}} > \frac{A_i}{(p^{\pi=0}_{j,i})^{\frac{1-\beta}{\beta}}}$$

The Quality advantage of the entrant must be higher than the price disadvantage, weighted by demand a demand parameter. To get the condition as a function of model primitives, insert the formula for the zero profit price:

$$\frac{p^{\pi=0}_{j,e}}{p^{\pi=0}_{j,i}} = \frac{\left[\frac{w_c}{\bar{q}} \cdot \frac{1}{S_e \cdot \bar{q}}^{\varepsilon_e} \cdot (LA_{j,e})^{\varepsilon_e}\right]^{\frac{\beta}{\beta+\varepsilon_e}}}{\left[\frac{w_c}{\bar{q}} \cdot \frac{1}{S_i \cdot \bar{q}}^{\varepsilon_i} \cdot (LA_{j,i})^{\varepsilon_i}\right]^{\frac{\beta}{\beta+\varepsilon_i}}}$$

$$\frac{p^{\pi=0}_{j,e}}{p^{\pi=0}_{j,i}} = \frac{\left[\frac{1}{S_e \cdot \bar{q}}^{\varepsilon_e} \cdot (LA_{j,e})^{\varepsilon_e}\right]^{\frac{\beta}{\beta+\varepsilon_e}}}{\left[\frac{1}{S_i \cdot \bar{q}}^{\varepsilon_i} \cdot (LA_{j,i})^{\varepsilon_i}\right]^{\frac{\beta}{\beta+\varepsilon_i}}}$$

$$\frac{A_e}{A_i} > \left(\frac{\left[\frac{1}{S_e \cdot \bar{q}}^{\varepsilon_e} \cdot (LA_{j,e})^{\varepsilon_e}\right]^{\frac{\beta}{\beta+\varepsilon_e}}}{\left[\frac{1}{S_i \cdot \bar{q}}^{\varepsilon_i} \cdot (LA_{j,i})^{\varepsilon_i}\right]^{\frac{\beta}{\beta+\varepsilon_i}}}\right)^{\frac{1-\beta}{\beta}}$$