Labor market power and innovation

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Abstract:

This paper examines how labor market power shapes firms' decisions to innovate and growth. 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. 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 predictions. When combining our model with the data, we find that the distortinary impact of labor market power on firms' innovation choices has a sizeable negative effect on aggregate productivity and can explain a substantial share of regional productivity differences in the German manufacturing sector.

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

1 Introduction

Throughout the developed world, union membership is declining (Katz and Autor, 1999) and the labor share is falling (Barkai, 2020; De Loecker and Eeckhout, 2018; De Loecker et al., 2020). This is partly explained by substantial increases in firms' labor market power, 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). Firms with high labor market power necessarily have to pay higher wages when they increase their size, which lowers aggregate productivity by 20% in the US (Berger et al., 2022) and 10% in Eastern Germany (Bachmann et al., 2022).

Apart from static distortions that monopsony causes, there is also a dynamic implication that has been less studied: Firms with high price setting power on the labor market are disincentivized from growing and thus investing in productivity increases. This dynamic distortion can be significant as a large part of the gains from firm productivity growth come from increasing firm size. The objective of this paper is to theoretically characterize the relationship between firms' monopsony power and innovation and to empirically quantify its impact on long-term productivity growth.

To achieve this, we develop an endogenous growth model in the spirit of Akcigit and Kerr (2018) in which firms invest in innovation to increase their productivity and size, which also drives the evolution of aggregate productivity. In the standard model by Akcigit and Kerr (2018), firms produce an intermediate input in imperfectly competitive output markets. The intermediate goods are then combined into a final product using a CES aggregator, which ensures tractability. The novelty of our model is that firms also face an upward-sloping labor (input) supply curve. This creates two opposing effects: On one hand, firms enjoy higher profits from becoming large due to their monopsony power, which allows them to mark down wages. 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 growth through innovation. It turns out that at a small firm size the former effect dominates, that is, small firms in monopsonistic labor markets, relative to competitive labor markets, have stronger incentives to grow as this allows them to better exploit their monopsony power. However, once firms are sufficiently large, the latter effects of increasing marginal and infra-marginal labor costs dominates and they are discouraged from innovation and growth.

As a result, the model predicts two empirical features that we validate in firm-level data and which otherwise would be unresolved empirical puzzles: Firstly, in monopolistic labor markets, small firms have comparatively high R&D expenditures whereas large firms' R&D expenditures are relatively small (large firms still have higher R&D expenditures than small firms). 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 monopsony power. The fact that our theory predicts these patterns and that we validate them in the data provide strong support for the mechanisms that we propose.

Empirically, we utilize German manufacturing firm-level data (1995-2018) which is ideally suited for our analysis for several reasons. 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 two independent empirical strategies. First, we use 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 is ideally suited for this analysis as it 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), De Ridder et al. (2024)).[1] Second, we measure firms' labor supply elasticity directly, exploiting exogenous shocks to firms' labor demand and information on average firm-level wages. Specifically, we use changes in the demand for manufactured goods on the world market, which increases firms' labor demand depending on the goods they can manufacture. We then observe the resulting changes in wages. Both strategies yield broadly similar results, though we can only use exogenous trade shocks for a subset of our data. To directly study innovation outcomes associated with labor market power, we also merge the EPO patent data base to our German data.

We find that firms in structurally weak regions have higher labor market power, are smaller and have lower R&D expenditures. In our German data, we show that these differences remain after controlling for sector and size. In addition, labor market power is strongly negatively associated with R&D expenditures, except for the smallest firms. Firms with high labor market power have a flatter profit profile with respect to productivity, i.e. their profits rise less if their productivity increases.

The German setting is ideal for studying these effects because the former German separation resulted in a persistent economic division, where wages and GDP per capita in East Germany are approximately 20% below the West German levels, even more than 30 years after the reunification of East and West Germany. We find that differences in labor market power with a considerably higher level in the East are equally persistent and show that this contributes to the productivity gap through lower innovative activity. However, our results are not only relevant for the German context. In Section 5 we discuss that the regional economic disparity in Germany is not a unique case. Instead, using comparable cross-country data on productivity, labor market power, and R&D investment for several European countries, we show (i) that regions exhibit vast differences in productivity that are inversely related to regional levels of labor market power (as in the German case), and (ii) that also R&D investment is negatively related to labor market power across European regions. These findings are consistent with

[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 (e.g., (Dobbelaere and Kiyota, 2018), (Mertens, 2020; Mertens and Mueller, 2022; Mertens, 2023), (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)).

the mechanisms that we highlight in the German context, suggesting that labor market power might have an important role in shaping regional productivity and income differences across Europe.

The remainder of the paper is organized as follows: Section 2 relates our study to the existing literature. Sectionsec:data describes our data sources. Section 3 describes our German manufacturing sector 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 discusses robustness checks and the relevance of our analysis beyond the German context. Section 6 concludes.

2 Literature Overview

Our results 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). We are not the only ones to 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 the incentives of firms to invest into R&D and therefore their long-term growth perspectives are shaped by LMP. 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 and the firms' motivation for innovation. 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 and Warzynski, 2012). 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. **?**). 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

[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.

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]

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, 2023; 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:

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

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:

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

[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 to an insufficient number of firms for estimating production functions.

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.1.1, 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 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

[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.

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).

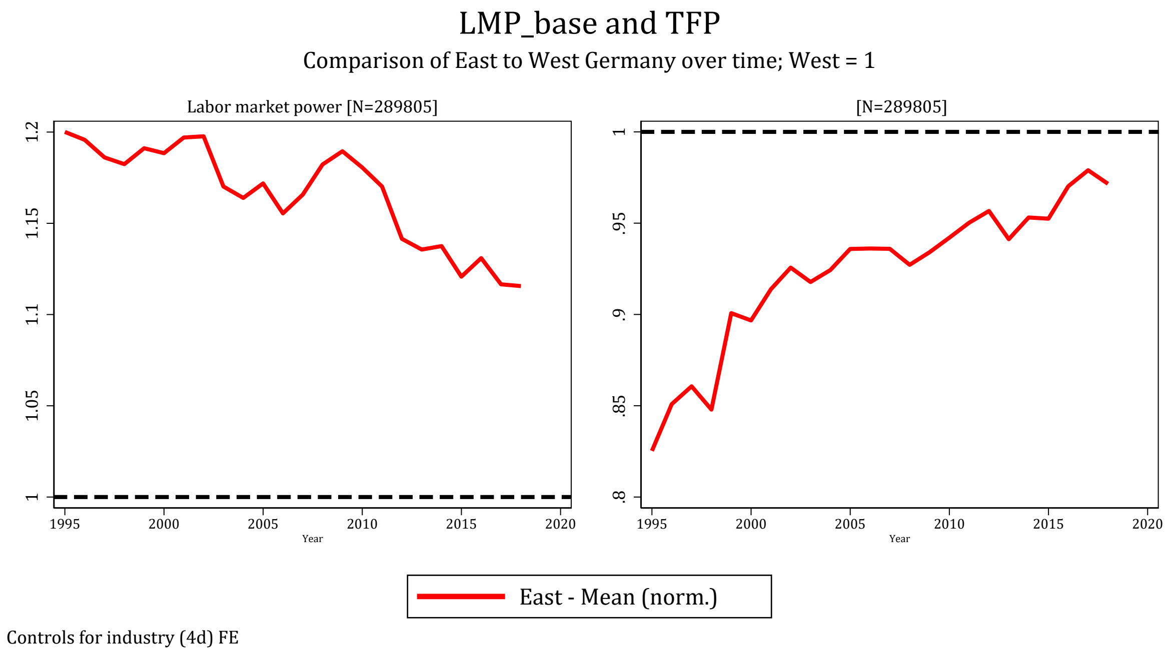
Discussion and Robustness: Hicks-neutrality. In line with prior work, the framework above assumes Hicks-neutral productivity to estimate labor market power and productivity. To address potential concerns regarding this assumption, we also use two alternative estimates of firms' monopsony power. First, 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 XXX. 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

[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).

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

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 time series for average firm labor market power and total factor productivity (TFP) after residualizing four-digit industry fixed effects. We document a significant and persistent productivity gap between West and East Germany. While it declines slightly during our sample period, the productivity gap remains sizeable and significant even more than 25 years after the German reunification in 1990.

In addition to these persistent productivity differences, our data shows similar differences in firms labor market power between East and West German firms. Over time, differences in labor market power narrow only slightly and remain persistent. Hence, the convergence processes, or lack thereof, are qualitatively similar to what we observe for productivity. Table 1 shows that the average East-West differences in firms' labor market power become even stronger when including additional controls for firms' employment and capital stock levels to account for firm size.

Table 1: LMP differences in Germany, Source: AFiD, own calculations

	Dependent variable:	
	Firm labor market power	
	(1)	(2)
East = 1	0.177***	0.214***
	(0.00588)	(0.00485)
Log labor		-0.000786
		(0.00301)
Log capital		0.154***
		(0.00199)
Observations	266,713	266,713
R-squared	0.241	0.495
Industry4d FE	Yes	Yes
Year FE	Yes	Yes
Firms	47394	47394

Fact 2: Firms with higher labor market power innovate less. Table **??** presents our core empirical result. The table displays a set of regression results from projecting firms' R&D intensity of firms' labor market power and a set of other variables, while controlling for industry and year fixed effects. Column (1) shows results from an initial regression where R&D intensity is regressed on log employment and log capital. It shows that larger firms have, on average, a higher R&D intensity which is expected as a majority of firms have R&D expenditures equal to zero and the larger ones are more likely to engage in R&D at all. Column (2) shows that there is a strong negative correlation between LMP and R&D intensity, which is key to our paper. 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. Column 3 shows that this result is virtually unchanged when controlling firm fixed-effects in the panel regression. Column (4) introduces an East dummy. Strikingly, the East coefficient is strongly *positive*, after controlling for LMP. Hence, LMP is higher in the East, but, apart from that, the East-dummy is *positively* correlated with R&D intensity. To further scrutinize the dynamics of labor market power, column (5) introduces an interaction between the labor market power and the East-dummy. Strikingly, labor market power has an even higher adverse correlation with R&D intensity in the East compared to the West. A potential explanation for this could be that labor market power is more systematic and more predictable in East Germany, exacerbating the innovation-dampening effect.

As a robustness Table 2 shows that our result holds at both intensive and extensive margins. Columns (1) and (2) replicate the main result from Table **??** for comparison. In (3) and (4) covers the extensive margin with a dummy outcome, which is 0 if a firm does not engage in R&D and 1 if a firm has positive R&D expenditures in a given year. On the extensive margin our result is qualitatively confirmed: Labor market power decreases the likelihood to engage

Table 2: R&D intensity and LMP: Intensive and extensive margin of R&D

VARIABLES	(1) R&D/sales	(2) R&D/sales	(3) R&D dummy	(4) R&D dummy	(5) log. R&D	(6) log. R&D
Labor market power	-0.772***	-0.869***	-0.0367***	-0.0419***	-0.164***	-0.142***
	(0.0482)	(0.0512)	(0.00669)	(0.00689)	(0.0327)	(0.0334)
East = 1		0.367***		0.0196***		-0.103***
		(0.0421)		(0.00594)		(0.0328)
l	0.274***	0.309***	0.111***	0.113***	0.895***	0.884***
	(0.0238)	(0.0242)	(0.00369)	(0.00374)	(0.0205)	(0.0208)
k	0.322***	0.320***	0.0444***	0.0443***	0.334***	0.335***
	(0.0176)	(0.0176)	(0.00266)	(0.00266)	(0.0165)	(0.0165)
Constant	-4.599***	-4.697***	-0.848***	-0.853***	2.941***	2.975***
	(0.210)	(0.211)	(0.0285)	(0.0286)	(0.179)	(0.180)
Observations	240,440	240,440	240,440	240,440	82,725	82,725
R-squared	0.226	0.228	0.297	0.298	0.625	0.625
Industry4d-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	No	No
Firms	39245	39245	39245	39245	14844	14844

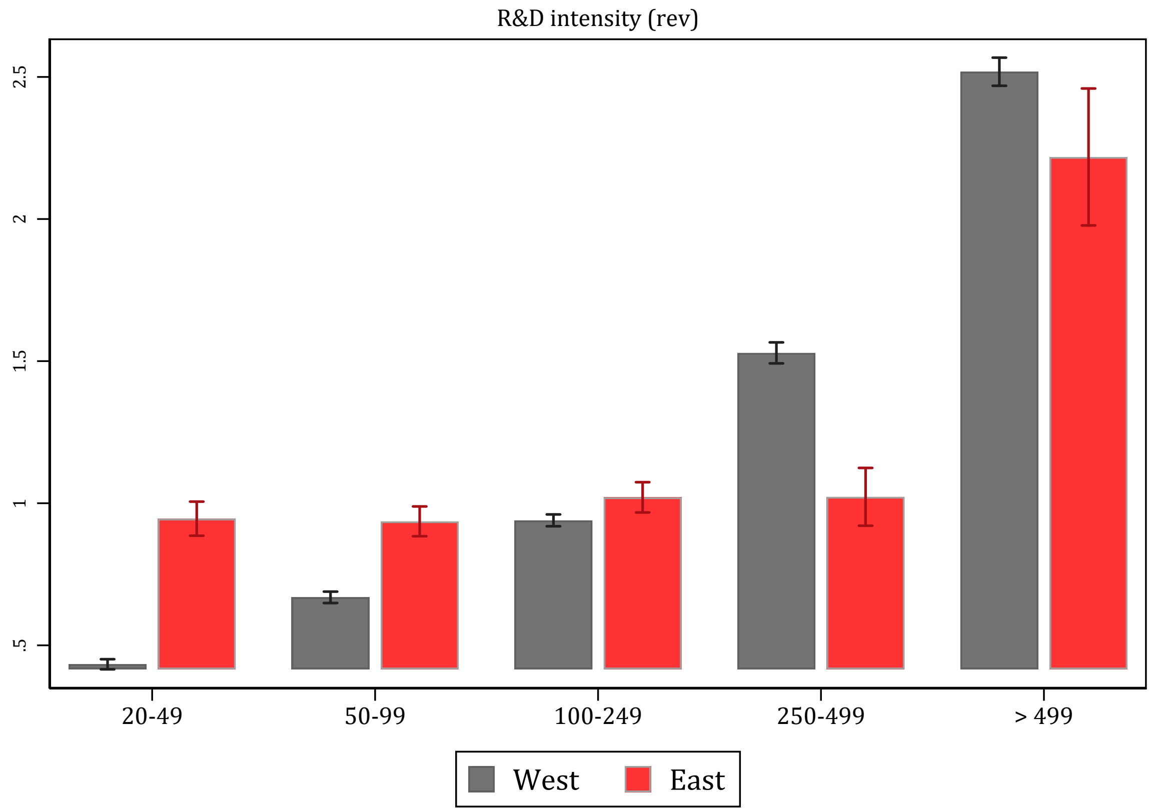
Model: base. Pooled OLS regression.
Clustered standard errors on firm level in parentheses.

in R&D significantly. Columns (5) and (6) repeat the exercise with log. R&D expenditures to test the intensive margin. Here, the main result - a negative correlation with the LMP measure - holds firmly, but the East effect turns negative. Together these results show that R&D is more likely in the East after controlling LMP, but this is driven by small firms with generally lower R&D expenditures. On the intensive margin, the East is lagging behind even after controlling LMP.

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 5 shows that LMP and R&D are generally negatively related, Figure 2 reveals interesting heterogeneities with respect to R&D 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 Fact 5 (the negative correlation of R&D with LMP), 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

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

Table 3: Correlation of R&D intensity and LMP, by firm size classes; source: AFiD, own calculations

VARIABLES	(1) 20-49	(2) 50-99	(3) 100-249	(4) 250-499	(5) More than 499
Labor market power	-0.695***	-0.841***	-0.896***	-1.237***	-1.887***
	(0.0856)	(0.0813)	(0.0721)	(0.138)	(0.202)
East = 1	0.601***	0.418***	0.323***	0.0649	-0.179
	(0.0640)	(0.0599)	(0.0641)	(0.135)	(0.355)
Constant	-1.971***	-4.657***	-6.094***	-9.629***	-18.50***
	(0.490)	(0.511)	(0.550)	(1.291)	(1.738)
Observations	63,028	61,482	62,317	27,588	26,152
R-squared	0.163	0.174	0.211	0.266	0.350
Industry4d FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Firms	16424	15094	12402	5200	3117

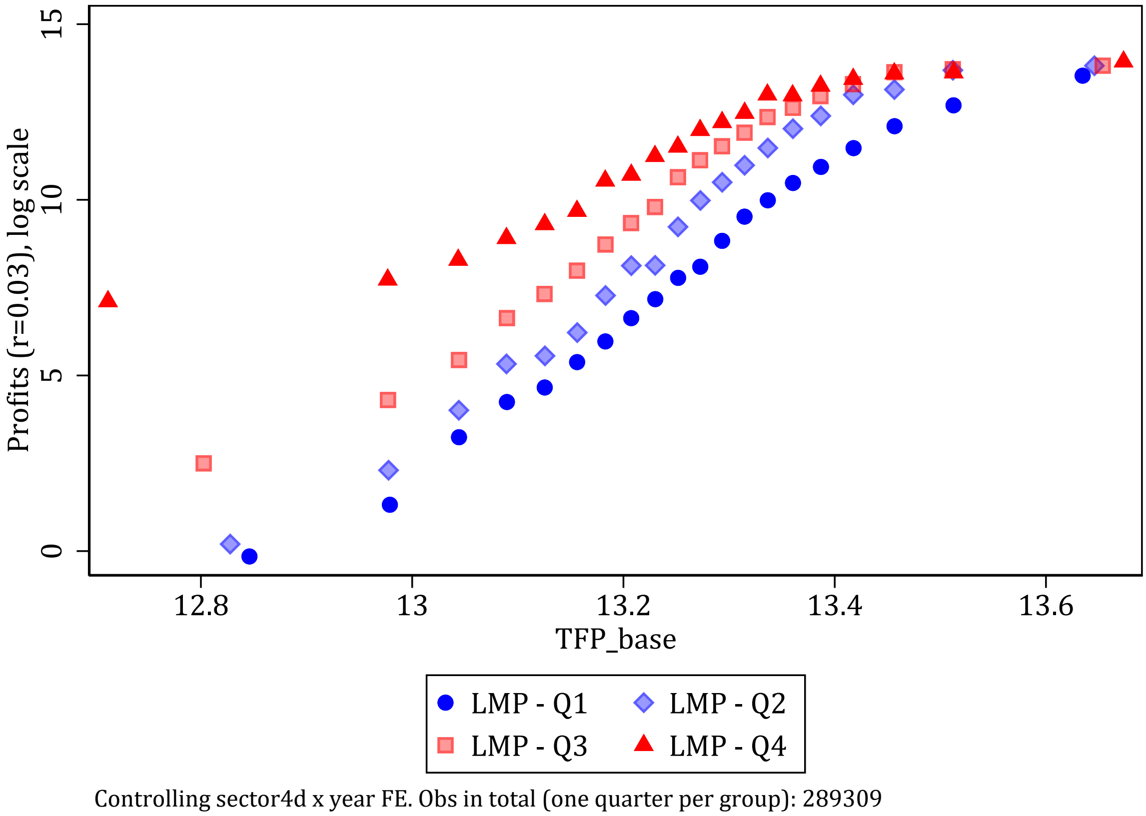
Dependent variable: R&D intensity (R&D/Sales)
Model: base. Clustered standard errors on firm level in parentheses.
Pooled OLS regression. Each column has results for different size class in terms of employment.

the incentives to invest and growth differently for large (high-productivity) and small (low-productivity) firms. As corroborating evidence for this, we re-run the regression from **??**, column (4) again in Table 3, but separately by firm size classes. We find that the coefficient of LMP increases with the firm size and the increasing R^2, albeit not directly comparable, hints at the LMP mechanism becoming more important in explaining variations in R&D intensity at larger firm sizes.

Fact 4: Productivity 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 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.

As expected, firms with higher productivity levels generate greater profits. Also, LMP generally increases profits: At all but the highest levels of TFP, the curves for the higher LMP quartiles are above the lower ones. But there is an important difference in the slopes of these curves: This Profit-TFP relationship is considerably flatter for high labor market power firms. While at lower levels of productivity, high labor market power firms generate relatively higher profits, their 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

Figure 3: Productivity and profits under different LMP regimes, source: AFiD, own calculations



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 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.

Summary. Summarizing this section, we find the following differences between East and West Germany:

1. Labor market power is higher in the structurally weaker East German region and persists in similar fashion to the TFP gap between East and West Germany.
2. The regional difference in LMP remains prevalent across heterogeneous firms and is not driven by composition differences in terms of industries or firm sizes.
3. Firms in East Germany are on average smaller.
4. Firm-level innovative activity is lower in East Germany.
5. Labor market power is strongly negatively correlated with R&D intensity. Accounting for this eliminates the R&D gap of the East and even reverses it on average.
6. The LMP effect is less important for small firms. Small firms in East Germany have comparatively higher R&D intensity compared to Western small firms.
7. LMP enables higher profits at given levels of TFP, but profit increases from TFP improvements are decreasing in LMP.

Given these empirical facts, we propose that labor market power has a dampening effect on innovation. While our empirical analysis does not allow for a causal identification of this effect, the strong evidence we present gives us confidence in our results. The ubiquity of LMP in the East, the lack of innovation and TFP growth, and the simultaneous persistence of both effects is striking. Furthermore, we find a size-gradient to these correlations: Smaller firms engage more in R&D, but cease doing so once they have grown larger. The negative relation between R&D and LMP is weakest for these smaller firms.

To explain this result we propose a mechanism, according to which the expected profits from labor market power initially incentivize firms to reach a certain size threshold at which firms can exploit workers optimally. Yet, once they have grown large enough, they have no further incentive to engage in innovation that would increase their productivity and size because this would cannibalize on their LMP-induced cost savings as they would demand more and more labor. The proposed mechanism hinges on the assumption that firms face upward sloping labor supply curves. This assumption is in line with monopsonistic labor markets and as Bachmann et al. (2022) show this framework fits the German case, in particular East German labor markets well. However, to make sure that our measure wage markdown is in line with monopsonistic labor markets also in our sample, which features manufacturing firms, we employ a second approach to measure differences in the labor supply elasticity between East and West Germany directly in Section 3.4, which yields a similar coefficient as the one implied by our markdown measure. A second crucial assumption is that firms cannot perfectly discriminate wages across workers. Given these assumptions, growing more productive in the presence of LMP is relatively less attractive as expansion incentives are limited. This is in line with our Fact 7: The relationship between profits and productivity is weaker for high-LMP firms. Profits hinge relatively more on exploiting LMP and less so on productivity, i.e. less on general efficiency or output quality. In Section 4 we develop a model that elucidates this mechanism through which LMP can influence firms' innovation decisions in a standard theoretical framework.

3.4 Robustness: 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 4 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 4: 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

4 Theoretical model

In this section, we develop an endogenous growth model that captures the mechanism through which LMP lowers the incentives to innovate and allows us to quantify the size of the effect. We rely on three main building blocks: First, imperfect competition on product markets ensures that firms with different productivity can exist in the market. Second, these firms face potentially heterogeneous, upward-sloping labor supply curves, yielding labor market power. Third, these firms invest in innovation to increase their productivity, which drives the evolution of aggregate productivity.

Our model mainly speaks to productivity improvements in existing product lines of firms, i.e., internal innovation of incumbents. However, the key mechanism can be derived under a setting were firms compete for product-line leadership as well, as long as developing a new product line entails an expansion of the existing workforce of the firm within the same labor market. This is because labor market power generally reduces the incentives of firms to grow, by creating a trade-off between the returns from innovation, which are coupled to increasing firm size, and the returns from monopsonistic exploitation, i.e., from staying smaller to mark down wages.

4.1 Demand

Conceptually, any demand structure that leads to imperfect product competition would yield the same qualitative behavior: The key interaction is between firms and workers on the input market. We use the demand structure of Akcigit and Kerr (2018) for its tractability, specifically, for the resulting linear relationship between profits and productivity for firms without labor market power. Representative households consume all goods and derive utility from this according to

$$U = \int_0^\infty e^{-rt} \ln(Y(t))dt \tag{5}$$

where r is the time preference parameter and $Y(t)$ is the final good of the economy. There is a final goods producing sector that creates $Y(t)$ from the intermediate products of the observed firms. This sector produces according to

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

where $L_c^{\beta}(t)$ is the amount of labor dedicated to final goods production, A_j is quality and z_j is quantity of variety j. The final goods producing sector consists of atomized firms and thus demands any specific variety according to

$$p_j = L_c^{\beta}(t) * A_j^{\beta} * z_j^{-\beta} \tag{7}$$

Thus, the price the final goods sector is willing to pay for variety j rises with its quality and falls with its quantity. The producer of variety j is a monopolist for that specific variety, but faces the indirect competition of the other producers. The monopolist produces with $z_j = \bar{A} * l_j$, i.e. the higher the average quality in the economy, the higher is the actual production, which keeps the economy on a balanced growth path. This production function poses a considerable simplification of the production process compared to our empirical framework, but this specification allows our model to remain tractable. First, we drop intermediate and capital inputs and focus on labor l as the only production input.[6] Second, given this one-input structure we also remove decreasing returns from the factor labor. This constant-returns-to-scale assumption serves mainly the tractability of our model, but importantly this assumption goes against our mechanism: If there were decreasing returns to the factor labor, our mechanism would be exacerbated as it would render returns to hiring additional workers even smaller. Finally, we let the firm produce at average productivity and instead model productivity improvements as quality improvements on the output market in. This allows us to follow the model from Akcigit and Kerr (2018) more closely and has the same implications as the Hicks-neutral TFP term in our empirical estimates: Improving quality A_j benefits the firm at large and not just its efficiency regarding a specific input.

Eq. 7 yields firms' profits as

$$\pi(A_j) = L_c^{\beta}(t) * A_j^{\beta} * (\bar{A} * l)^{1-\beta} - w(l_j) * l_j \tag{8}$$

Revenues are rising in product quantity and thus also production employment l_j. However, the increase is less than linear, which will lead to an optimal firm size. The demand parameter β (substitutability of product variants) is an important determinant of the size differences between firms in equilibrium. The second determinant is $w(l_j)$, which denotes the endogenous wage that the firm pays on its labor market. This is the only difference relative to the original paper, where the labor market is competitive and there is an economy wide wage $w^c = \bar{A}$. The more $w(l_j)$ responds to the firm's labor demand, the lower the size differences between firms will be.

4.2 Production and labor markets

Workers are associated with firms by preferences: Due to geography, work topics or other mechanisms, workers prefer to work for a specific firm such that firms experience an inverse labor demand of

$$w(l_j) = w^c * \min\left(1, \left(\frac{l}{S_j}\right)^{\varepsilon}\right) \tag{9}$$

The labor market power situation of each firm is characterized by the size of its pool of attached workers S_j and the elasticity of worker preferences ε. Both Maassen et al. (2024) and Bachmann et al. (2022) use these types of preferences. After a firm has used up its individual pool of workers, S_j, over which it has labor market power, we allow the firm to higher

[6] In the absence of perfect factor substitution, i.e. as long as firms need workers to operate at all, our mechanism holds. However factor substitution could mitigate the effects to some extent.

workers from a residual market at the market wage. This is another simplifying assumption. Essentially we remove a punishment for exceeding S_j, which would again exacerbate our mechanism. If firms had to pay higher-than-market wages to attract less willing workers, their incentive to increase firm size would be even lower. But most importantly this assumption allows us to solve our model analytically as all firms can potentially enter the region where profits are linear in quality A_j, if their quality and therefore size is large enough. The benchmark competitive wage w_c is normalized to unity in the remaining parts of the model.

4.3 Static profit maximization

To maximize their static profits, firms have to choose the optimal labor l_j. Insert equation 9 into 8 and optimize w.r.t labor l_j to arrive at optimal labor $l_j^* = \left[\frac{(1-\beta)\Phi A_j^{\beta}(S_j)^{\varepsilon}}{(1+\varepsilon)}\right]^{\frac{1}{\varepsilon+\beta}}$.[7] That is, equilibrium labor is increasing in productivity and the size of the firm's worker pool and declining in product substitutability. The wage elasticity ε has an ambiguous effect on firm size: If productivity is very low, the firm might actually increase production above what it would do in a competitive equilibrium to maximize the gains from its labor market power.

To understand the relationship between our model and the empirical exercise in section 3, we can use this optimization result: our measure of labor market power γ is defined as the ratio between the marginal revenue productivity of labor and the wage, which is

$$\gamma = \frac{\frac{\partial rev(l)}{\partial l}}{w(l)} = \frac{\left(\frac{l}{S_j}\right)^{\varepsilon}(1+\varepsilon)}{\left(\frac{l}{S_j}\right)^{\varepsilon}} = (1+\varepsilon) \tag{10}$$

i.e. our empirical measure γ exactly recovers the labor supply elasticity ε. This highlights that equation 9 implies a constant labor supply elasticity faced by the firm.

The equilibrium employment l_j^* also implies equilibrium profits as

$$\pi(A_j) = \pi^*(\varepsilon) \cdot A_j^{\frac{\beta(1+\varepsilon)}{\varepsilon+\beta}} \tag{11}$$

Where π^* is a complicated constant function of the model parameters, including ε. This result is analogous to the original Akcigit and Kerr (2018), where profit was linear in productivity. Note that in the special case of $\varepsilon = 0$, profit is linear in A_j and the model collapses to its predecessor. The additional curvature in profits is introduced by the labor market, where unproductive firms can reap additional profits by wage markdowns. When ε is positive, firms' profits hinge to less extent on productivity, as the exponent of A_j drops below 1. At the same time the constant profit term increases in ε. Therefore profits are generally higher for firms with higher labor market power, when productivity and firm size are low, but this advantage dissipates when productivity increases. The returns to increasing productivity, as can be seen from the exponent of A_j are lower in the presence of labor market power. Panels 1 and 2 of Figure 4 illustrate firm revenue and profits as a function of productivity A_j.

[7] Φ is a from the firm's perspective given and defined as $\Phi = \frac{L_c^{\beta}\bar{A}^{1-\beta}}{w_c}$

4.4 Technology and R&D Decision

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

$$R(z_j, \bar{A}) = \hat{\chi} * z_j^{\hat{\psi}} \bar{A} \tag{12}$$

Expenditures $R(z_j, \bar{A})$ rise linearly with the current technology level of the economy $\bar{A}$ 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.

Since R&D expenditures rise linearly in $\bar{A}$ – the same as the productivity gains from innovation $\bar{A} * \lambda$ –, equilibrium innovation behavior of the firms will not depend on the level of innovation and the economy will expend a fixed share of GDP on R&D, resulting in a fixed growth rate.

4.5 Dynamic Optimization

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

$$\begin{aligned} r * V(A_j, \varepsilon, \bar{A}) - \dot{V}(A_j) = \\ max_{z_j}(\pi^* * A_j^{\frac{\beta(1+\varepsilon)}{\varepsilon+\beta}} - R(z_j, \bar{A}) + z_j[V(\lambda * \bar{A} + A_j) - V(A_j)]) \end{aligned} \tag{13}$$

where the value of the firm is driven by the current profits $\pi^* * A_j^{\frac{\beta(1+\varepsilon)}{\varepsilon+\beta}}$, the costs of R&D $R(z_j, \bar{A})$ and the arrival rate of innovations times value of potential innovations $z_j[V(\lambda * \bar{A} + A_j) - V(A_j)]$. 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.

However, if $\varepsilon = 0$, the profit function and thus also the value function is linear. To see this, use guess and verify: We guess that the value function is $V(A_j) = \kappa * A_j + \Xi * \bar{A}$. Then eq. 14 becomes

$$r * V(A_j) = \pi^* * A_j - R(z_j, \bar{A}) + z_j[\lambda * \kappa * \bar{A}]$$

Optomizing with respect tot he rate of innovation z_j^* gives

$$z_j^* = [\frac{\lambda * \kappa}{\hat{\chi} * \psi}]^{\frac{1}{\hat{\psi}-1}}$$

Thus, z_j^*, firms have the same R&D expenditures, irrespective of productivity/quality A_j, rising linearly in $\bar{A}$. We can insert this into the value function to arrive at

$$V(A_j) = \underbrace{\frac{\pi^*}{r}}_{\kappa} * A_j + \underbrace{[\frac{\lambda^{\hat{\psi}} * \frac{\pi^*}{r}^{\hat{\psi}}}{\hat{\chi}\hat{\psi}}]^{\frac{1}{\hat{\psi}-1}}[1 - \frac{1}{\hat{\psi}}]\frac{1}{r} * \bar{A}}_{\Xi} \tag{14}$$

Which confirms the guess of a linear value function in A_j and $\bar{A}$. The first term denotes the value of the currect quality of the firm and the second term denotes the option value of innovation, which depends on the overall technology level because that determines both step size and costs of innovation.

However, this requires labor market power ε to be 0. To carry over 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:

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

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

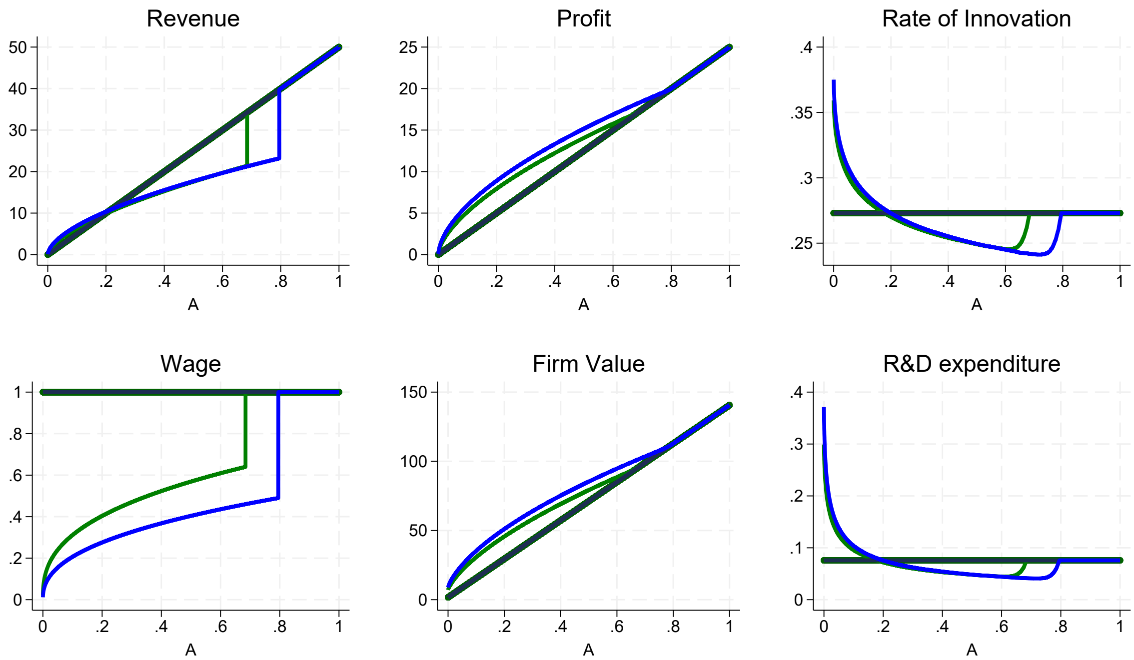
$$max_{z_j}(\pi^* * A_j^{\frac{\beta(1+\varepsilon)}{\varepsilon+\beta}} - R(z_j, \bar{A}) + z_j[\kappa(A_j + \lambda\bar{A}) + \Xi\bar{A} - V(A_j, \varepsilon, \bar{A})]) \tag{15}$$

Since 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 4 reports firms' strategies and evaluation for different levels of ε.

Reviewing firms' strategies, high labor market power firms mostly are smaller, less innovative and pay lower wages for a given productivity, replicating the aggregate characteristics of structurally weak regions. However, this is not true for very unproductive firms: These firms are both more innovative and larger for a given productivity. Both choices are driven by their labor market power: Low productivity firms increase production beyond what their product would warrant to gain profits from their wage markdowns and they invest more in R&D in order to be able to profit even more in the future. This is reflected in the profit and value functions: Initially, both profits and values rise faster than without labor market power. However, they then converge back to the competitive functions from above. Thus, the gains from innovation are initially higher for high labor market power firms, but then decline below that of no labor market power firms. The equilibrium R&D expenditures and the innovation rate reflect this: Very unproductive firms innovate more, but afterwards innovation declines.

The mechanism laid out in this static framework is the core mechanism that will lead to

Figure 4: 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

different growth outcomes in such a model. With research costs making the returns laid out in **??** costly to attain, the negative effect of labor market power, can well prove prohibitive to innovation at all. Certainly, it will lower innovation efforts. With a DGE model we can also quantify the returns to innovation better for firms with and without labor market power as in the preliminary results of **??**. Therefore, our empirical results are already mirrored in this foremost static framework: We found LMP to be consistently higher in East Germany compared to West Germany (empirical facts 1 and 2). In our model this reflects as a higher parameter value of ε for the East. Given this observation, our framework can generate the remaining results: Since, in this simplified model, productivity A_{it} is a direct correlate of firm size (**??**), our model clearly generates smaller firms sizes under LMP than in the competitive labor market. Fact 3 documented this empirically, and through this mechanism we link empirical result to the prevalence of labor market power. With our mechanism, observed productivity differences can then also be seen as an outcome, not only as a cause of the differences in firm sizes across East and West. Both our empirical result and this feature of our model is in line with the argumentation in Bachmann et al. (2022), although they do not measure firms' labor market power explicitly.

The main novelty of our analysis shows how LMP disincentivizes innovative activity. This reflects our empirical fact 6, showing a strong negative correlation between LMP and R&D intensity. It should be noted that R&D is only one option how firms can improve their Hicks-neutral productivity. Especially small firms might instead favor different productivity enhancement methods, such as adopting technology or learning best practices. Therefore, one could even view our negative correlation between R&D and labor market power as a lower bound. Our model also shows that this effect is expected to be different across firm sizes. As we document in Fact 5, small firms in East Germany actually invest more into R&D than their Western counterparts. Since firms' labor market power leads to short-run higher profits, in particular at low levels of size (or productivity), initially productivity improvements are especially lucrative for firms with high labor market power (empirical fact 6). However, these relatively higher profit gains quickly diminish, as seen in Figure 4. As large firms are the main contributors to R&D activity in general and R&D expenditures in particular, the pronounced dampening effect of LMP on R&D at large firm sizes is especially important for aggregate growth outcomes.

5 Discussion

In this section, we shortly describe robustness checks we conducted to address potential concerns in our analysis. Furthermore, we provide suggestive evidence that the mechanism we investigate for Germany also plays a role in other large advanced economies, exhibiting within-country differences in productivity and GDP per capita.

5.1 Robustness of empirical analysis

We conducted most of our empirical analysis using headcounts as our measure of labor. This is an imperfect measure because it comprises non-full-time employees which subsequently would be paid accordingly lower. This could in principle lead us to overestimate our measure for labor market power because we derive it from the ratio of the labor elasticity to total labor costs based on firms' number of employees. However, all of our results are robust and virtually identical if we use full-time-equivalents (FTEs) instead of headcounts. For a replication with FTEs of our main result from **??** see Table D1. Unfortunately, FTEs are only available beginning from the year 1999 in our data. To encompass earlier years, where possible, and to enable our production function estimation also for the year 1999, we therefore use headcounts in our baseline specifications.

Furthermore, our baseline measure for innovation is R&D intensity, i.e. R&D expenditures over revenues. However, our results are qualitatively and in most cases quantitatively robust to using different measures for innovative activity: We can define R&D intensity also in terms of value-added or number of employees, which leads to virtually identical results. Alternatively we can study patent intensity. This captures the output side of R&D activity, but at the same time captures only those innovations that are subsequently patented. For patent intensity we find qualitatively similar results of labor market power, which can be seen in Table D2, but the coverage of the patent data is currently limited in more recent years and exhibits generally more noise than our administrative data source on R&D expenditures. In future revisions of this paper, we will work with updated and more comprehensive patent data up until the end of our sample period, 2018, allowing us to test the robustness of our results more rigorously.

Our baseline specification for the production function has been estimated separately for industries, but across all years and both regions simultaneously. As a robustness check, we have estimated the production function again with two important changes: We estimate it for rolling seven-year windows, allowing for more fundamental differences over time in the underlying production technologies, and separately not only by two-digit industries, but additionally by East and West Germany. The results of this estimation exhibit more noise in all measurements which is mainly due to the lower number of observations per seven-year-industry-region cell. Similarly, for many smaller industries, especially in East Germany, the number of observations is too low to obtain any estimates. Nonetheless, even with this extremely complex and less stable estimation routine, we validate our key result from **??**. This can be seen in Table D3.

5.2 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 difference 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 5 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 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 6 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.

6 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 overall production output, we develop a framework in which labor market power can dynamically influence firms' decisions to conduct R&D and to innovate. We propose that this has an adverse effect on aggregate productivity growth and could cause development disparities, such as those seen between East and West Germany, in terms of productivity, wages and GDP.

To study the relationship between labor market power and productivity-enhancing R&D investments of firms, we use rich German manufacturing-sector firm-level panel data that al-

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

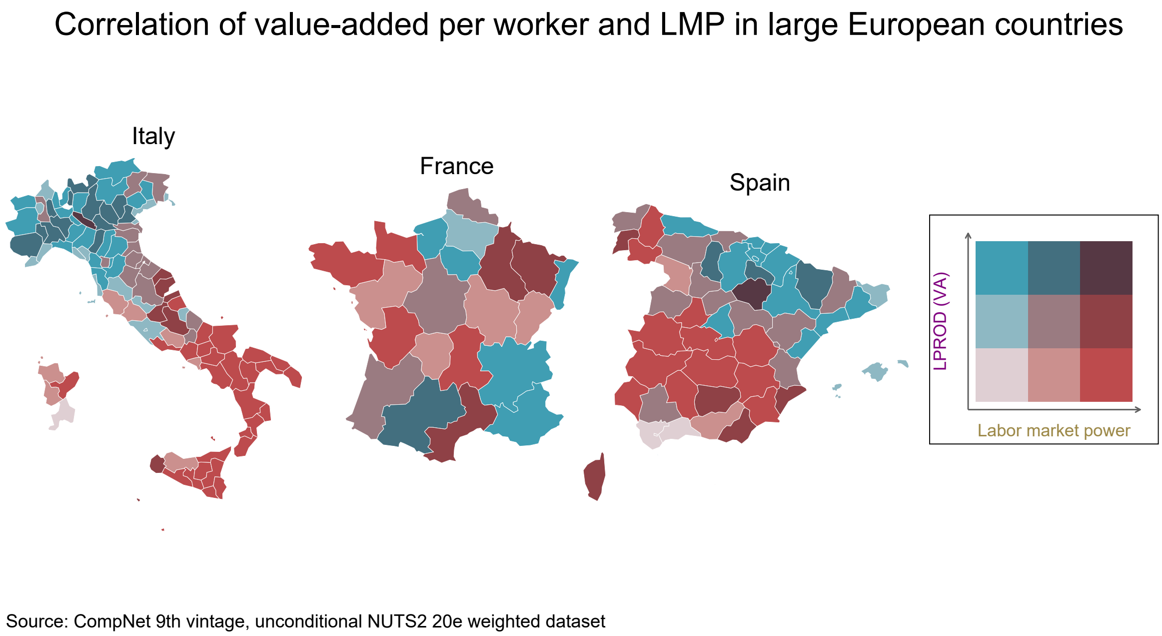


Figure 5: Labor market power and labor productivity in large European countries

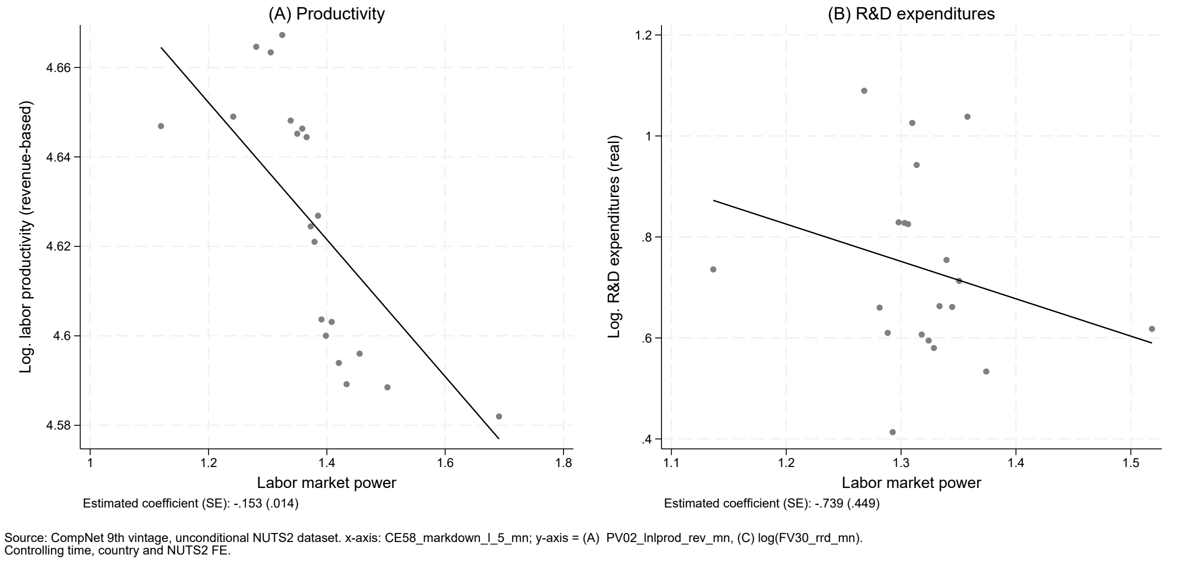


Figure 6: Labor market power, productivity and R&D across regions in 19 European countries

lows us measure firms' R&D activity and to estimate state-of-the-art measures of firm-specific labor market power and total factor productivity. Using this data, 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 rationalize this key fact as well as several other empirical findings using a simple model in which firms' incentives to invest into R&D are shaped by their labor market power. The model can replicate the above observations as well as many other empirical regularities regarding firms' labor market power in Germany.

While we focus on the German case, additional European 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.

In a planned extension of this paper we aim to investigate whether firms also specialize in different technologies that directly influence their labor elasticity and thus their returns to employing labor in production. For this we plan to classify linked patents into labor-augmenting and -replacing technologies to see whether on top of doing less innovation firms with labor market power also do different innovation.

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. The setting in the main text focuses on a monoposonistic setting that we detail in Appendix B.1.1. In **??**, we show that our empirical measure of labor market power can 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.

B.1.1 Main setting: Monopsony

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 prices. We use this price index to deflate observed firm revenue.[12] We construct firm-specific

[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.

[12] This approach has also been applied in other studies (e.g., **?**, **?**.)

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)):

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

$B(.) = B((pi_{it}, ms_{it}, G_{it}, D_{it}) \times \tilde{\boldsymbol{\phi}}_{it}^{c})$ 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}). $\tilde{\boldsymbol{\phi}}_{it}^{c} = [1; \tilde{\boldsymbol{\phi}}_{it}]$, 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 $\tilde{\boldsymbol{\phi}}_{it}^{c}$ 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 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 lo-

[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 **?**, 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.

cal 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 **?**: $\omega_{it} = h(\omega it-1, \mathbf{Z}_{it-1}) + \xi_{it}^{tfp} = f(.) + \xi_{it}^{tfp}$, 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:

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

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_{it}^{tfp}. 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:

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

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:

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

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

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

$\boldsymbol{\Psi}(.) = \sum_{n=0}^{3} \sum_{w=0}^{3-b} \sum_{h=0}^{3-n-b}\ l_{it-1}^n\, k_{it-1}^b\, e_{it-1}^h$.

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 Robustness checks

Table D1: Correlation of R&D intensity and LMP: FTE version; source: AFiD, own calculations

	(1)	(2)	(3)	(4)	(5)
VARIABLES	R&D/sales	R&D/sales	R&D/sales	R&D/sales	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 D2: 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 D3: 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.