Labor market power and innovation
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Abstract: This article studies the effect of labor market power (LMP) on firms' innovation decisions and aggregate growth. To examine the effect of LMP on innovation and productivity, we use rich firm-level data for the German manufacturing sector (1999-2016), which is characterized by strong regional East-West differences in productivity, innovation activity, and labor market power. Utilizing this data, we estimate the firm-level relationship between labor market power and innovation. In this static relationship, a one standard deviation change in LMP explains a differential of 10% of firm-level R&D spending. As a result, Eastern firms are less productive, smaller, but not necessarily less profitable. We then derive a model that theoretically characterizes the relationship between labor market power and firm innovation. Our theoretical framework provides an explanation for the patterns we observe: Firms with high labor market power generally have fewer incentives to innovate grow as their profit function depends to a relatively lesser extent on TFP. Yet, to benefit the most from labor market power firms have to reach an optimal size which implies that gains from innovation are indeed high at low productivity levels. At medium to large productivity levels and according firm size, this effect reverses as firms start cannibalizing on their labor market power. With this new channel and its implication on firm dynamics we provide a new explanation for the persistence of lower productivity and high average firm labor market power in structurally weak regions, such as East Germany.

JEL: D24, O31, J42, L10, L60

1 Introduction

This article studies the effect of labor market power (LMP) on firms' innovation decisions and productivity growth. Innovation is the main driver of sustained growth in the economy, but it requires firms to engage in costly R&D. Yet, a profit-maximizing firm will only make this investment if the additional profits earned through improved technology exceed the costs of R&D. The main objective of this paper is to study how firms' incentives to invest into R&D are shaped by their labor market power. We study this relationship in the context of East and West Germany, where we observe the well-documented productivity and wage gap and link it to a similarly persistent gap in labor market power. We propose that these two findings are related due to a dampening effect of labor market power on firm innovation. LMP reduces firms' incentives to grow and therefore the returns to innovation cannot be fully appropriated.

To arrive at this conclusion, we use state of the art estimators for total factor productivity (TFP) and labor market power in a comprehensive panel data set of German manufacturing firms covering the years from 1995 to 2016, following Mertens (2022). In a first step, we use the data to establish a series of stylized empirical facts. In particular, we show that:

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. Profit increases from TFP improvements are declining in firms' labor market power.

Having established these facts, we build a simple static model that allows us to study the relationship between firms labor market power and innovative activity. In the model, firms produce an intermediate input that on imperfectly competitive output and labor markets. The intermediate goods are then combined into a final product using a CES aggregator, which ensures tractability. Using the model, we study how changes firms' profits are shaped by productivity growth and labor market power.

Our model reveals that firms with relatively low productivity levels benefit particularly strongly from growing/increasing productivity as this allows them to exploit their labor market power. This raises these firms incentives to innovate, consistent with the fact that small East-German firms, that have relatively higher labor market power than their Western counterparts, invest relatively more into R&D than small West-German firms. However, for higher productivity levels, the relationship reverses and large, highly productive firms are, relative to a competitive labor market scenario, discouraged from investing into R&D if they have labor market power. This is because increasing their size further would cannibalize on large firms gains from labor market power. As a result, large, highly productive firms invest less into R&D if they have labor market power, which is consistent with the lower R&D investment rates of large East German firms compared to large West German firms that we observe in the data.

To bring our model to the data, we empirically recover the relationship between profits and productivity for different segments of firm to show that firms with high labor market power have higher profits, but that their profits rise slower with higher productivity. Specifically, we estimate firms' value functions with and without innovation from these findings, following Peters et al. (2017).

Using our framework, we document that firms in East Germany, with typically higher labor market power, gain on average between 0.3 and 0.7 Million Euro less from innovation compared to their West German equivalents. This relationship is reversed for low-productivity firms: Low-productivity East German firms gain about 1.5 Million Euro more, because innovation allows them to grow to a moderate size and profit from the high labor market power environment. This reflects firms' actual behavior as postulated by our mechanism: The least productive and smallest East German firms innovate more than their West German counterparts, but large East German firms innovate substantially less than their counterparts in the West because these firms' labor market power limits their incentives to grow. Put differently, large East German firms with labor market power specialize in exploiting labor to remain profitable, which leads to an environment in which Eastern firms have low productivity and pay low wages, while still being able to profitably compete through saving wage costs. This result is the main contribution of our paper.

The German setting is ideally suited to study these effects because the former German separation resulted in a persistent economic division, where wages and GPD per capita in East Germany are approximately 20% below 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 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. 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. In this section, we also use bring the model to the data to estimate the value function of both high and low labor market power firms, taking into account the possibility of future type switches in terms of firm labor market power and the effect of current and future innovation. Section 5 discusses robustness checks and the relevance of our analyzes beyond the German context. Section 6 concludes.

2 Relation to existing literature

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 effects firms business model. 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 building on De Loecker et al. (2016), following Mertens (2022) closely. However, we are the first to use these estimation techniques to explore the relationship between labor market power and innovation.

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 these techniques to study the effect of market power on firms' innovation decision.

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 (Barkai, 2017; 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. Akcigit and Kerr (2018)). To our knowledge, we are the first to analyze the dynamic innovation incentives of firms with labor market power.

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

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

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

3 Empirical Analysis

This section starts with a description of our administrative firm dataset and its contents.Section 3.2 explains how we estimate labor market power to study the empirical relationship between firms' labor market power, investment into R&D, and productivity. Finally, Section 3.3 presents a number of empirical facts which show the importance of labor market power and link it to innovation activity. We aim to capture these facts in our subsequent model framework.

3.1 Data

Main data: German manufacturing firm-level data. Our empirical analysis is based on the *AFiD data*, an administrative and representative panel of German manufacturing firms covering the years 1995-2018.[1] The data is collected and provided by the German statistical offices and comprises all manufacturing firms with at least 20 employees. The data includes information on firms' employment, outputs, input expenditures, investment, including R&D expenditures, and, most notably, output sales, quantities, and prices of firms' individual products. 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 and overview on all variable definitions used in our article; and Appendix Table A2 provides associated summary statistics for key variables separately for East and West Germany.[2]

Supplementary data: EPO patent data. We augment this data further with an additional information source on firm-level innovation: Patents. To achieve this, we select German patent applications filed between 1995 and 2016 at all major patenting authorities, which are provided by the European Patent Office (PATSTAT 2016b). These patent applications contain detailed information on patent applicants, incl. names and addresses. We then use a string matching algorithm to match the name strings to AMADEUS, a large and (for identifiers) comprehensive database of European firms, to retrieve a business registry number for these patent applicants. Lastly, we utilize this registry information to match the patent applications reliably to our administrative data set. We have identified 25116 applicants in AMADEUS, covering 80% of patents by German applicants. Of these, 67.8% are then directly linked to our manufacturing firm sample which corresponds to 35% of the firms in our main sample. Since many firms, even in the manufacturing sector, never patent, this match rate gives us high confidence that we have matched patent activity appropriately. Finally, we set the number of patents to 0 for firms in our sample, that remained unmatched and where we consequently do not observe patents for a given year.

3.2 Estimating labor market power and productivity

Labor market power. The key question in our this study is how labor market power affects firms' incentives to invest into R&D. To derive a measure of firms' labor market power, we

[1] 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.

[2] Due to the high data quality, We clean our raw data with respect to outliers conservatively. We define the following ratios and clean firm-year observations that are in the bottom or top 0.5% tails of the distributions of these indicators: value-added over revenue and revenue over labor, capital, intermediate input expenditures, and labor costs, respectively. We do not clean R&D expenditures, because we want to capture the entire bandwidth of innovative activity, which is concentrated at the top of the distribution. 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, 23, and 37 due to an insufficient number of firms for estimating production functions.

follow an established literature that uses the so-called "production approach" to estimating labor market power. Using a static cost-minimization framework, the literature has shown that firms' optimal input decisions for labor and intermediates contain information on firms' labor market power (e.g., Dobbelaere and Mairesse (2013), Mertens (2022, 2023) Yeh et al. (2022)). Denote firms' production function by:

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

where Q_{it} represents total physical output and L_{it}, K_{it}, and M_{it} denote labor, capital, and intermediate inputs used in the production of Q_{it}. Firm-specific total factor productivity is assumed to be Hicks-neutral and denoted by A_{it}. i and t index individual firms and years. We specify production in a general form and will later rely on a *translog* production function for the estimation. The only formal requirement is that $Q(.)$ is twice differentiable.

Firms maximize profits:

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

where P_{it} denotes the output price and 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. Intermediate (and capital) input prices are exogenous to firms. For the remainder of the discussion, we also abstract from potential capital market imperfections, which are not the the focus of our analysis. Although we do not explicitly analyze product markups, we 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:

$$\gamma_{it} = \frac{MRPL_{it}}{w_{it}} = \frac{\theta^L_{st}}{\theta^M_{st}} \frac{z_{it}M_{it}}{w_{it}L_{it}}, \tag{3}$$

where θ^L_{it} and θ^M_{it} are the output elasticities of labor and intermediates, respectively. In a competitive setting, the wage equals the marginal revenue product of labor. If the firm has labor market power, it pays wages that are lower than $\frac{\partial P_{it}(Q_{it})Q_{it}}{\partial L_{it}}$.[3]

[3]While our method allows for labor market power to be held by firms or employees, we find more evidence overall for the former, especially in East Germany. Therefore, our theoretical model in Section Section 4 focuses on a case where firms have monopsonistic labor market power, which is consistent with our estimation method and our findings. Nonetheless, in Appendix B.1.1 we show that we can derive the same labor market power expression also from a bargaining model, where workers have labor market power themselves. The latter can help rationalize why the literature regularly documents a significant share of firms with wages exceeding marginal revenue products. In our analysis, we interpret firms that face this scenario as firms with low LMP. For a setting that combines firm- and worker-side labor market power, we refer to Mertens (2023).

Estimating production functions and productivity. Measuring labor market power according to equation (3) requires an estimate of the output elasticities of labor and intermediates. Moreover, we are also interested in studying how firms' total factor productivity responds to changes in firm labor market power. To recover output elasticities and total factor productivity, we estimate firms' production function. We apply an established control function approach following the literature based on the seminal paper by Olley and Pakes (1996). Specifically, we apply a version of the one-step estimator from Wooldridge (2009) following previous work using the same data (Mertens (2022), Bräuer et al. (2023)). Below we summarize the key steps, 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:

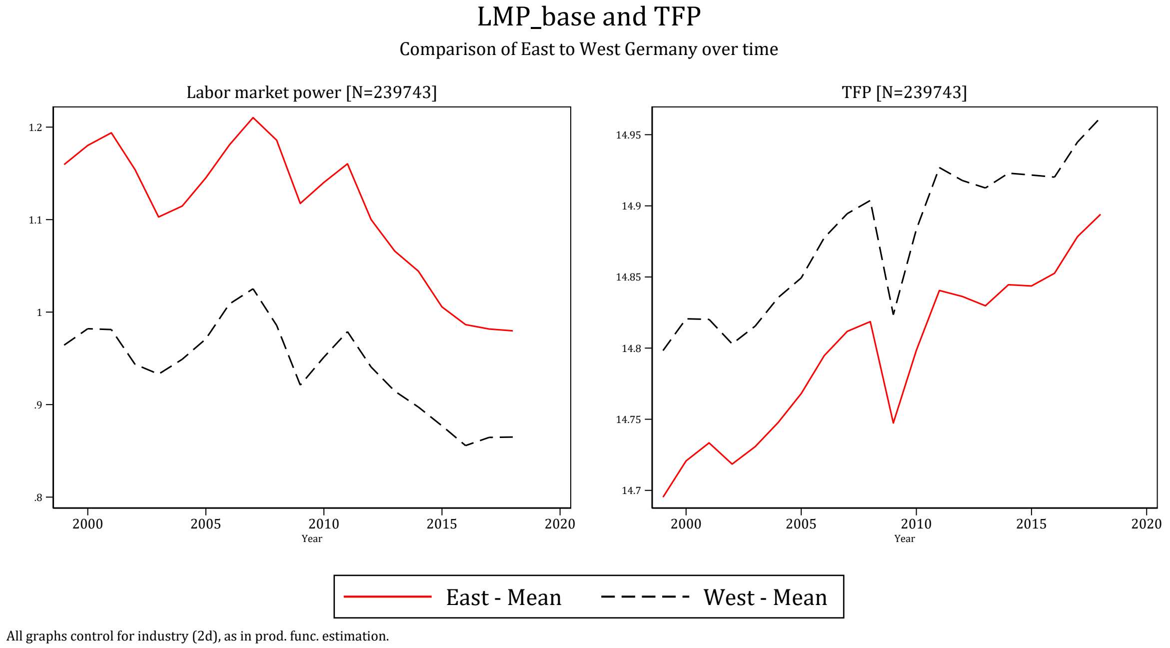
$$
\begin{aligned}
q_{it} = {} & \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \beta_{l2} l_{it}^2 + \beta_{k2} k_{it}^2 + \beta_{m2} m_{it}^2 + \\
& \beta_{lk} l_{it} k_{it} + \beta_{lm} l_{it} m_{it} + \beta_{km} k_{it} m_{it} + \beta_{lkm} l_{it} k_{it} m_{it} + a_{it} + \epsilon_{it},
\end{aligned}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

where lower-case letters denote that the inputs are measured in 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, similar to Levinsohn and Petrin (2003). As the literature has highlighted, estimating the production function with such an approach will tyipically yield to biased estimates as output and input prices of firms are unobserved and correlated with input decisions and output quantities (De Loecker et al., 2016). To account for firm-specific output price variation, we follow Eslava et al. (2004) and derive a firm-specific output price index from our firm-product-level price data that we use to deflate firm revenue which yields a quasi-quantity measure of output. To control for unobserved input price 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.

Having estimated the production function, we 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 quantity-based production factors and their interactions from Eq. 4 (i.e., all terms except a_{it} and ϵ_{it}).[4] Furthermore, we esimtate output elasticities for each primary production factor, X_{it} as $\frac{\partial q_{it}}{\partial x_{it}}$, with $x_{it} = \{l_{it}, k_{it}, m_{it}\}$ and report industry-specific average output elasticities in appendix **??**. Average output elasticities for capital, intermediates, and labor inputs equal 0.11, 0.64, and 0.30, respectively. Finally, we derive our labor market power expression from the estimated output elasticities using Eq. (3).

[4] We explain in Appendix C how we use firm-specific price information to account for firm-specific input price differences.

Figure 1: Labor market power and productivity differences



Notes: Evolution of avg. labor market power and TFP over time for East and West Germany. 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

3.3 Empirical Facts

This chapter summarizes key facts on East and West German firms labor market power, productivity, and R&D activities that will motivate our theoretical analysis.

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 two-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.

Fact 2: LMP is higher for East German firms across most industries and size classes. Figure 2 shows that higher East German wage markdowns, our measure of LMP, are a common feature across almost all two-digit industries in our data. In the only few exceptions, LMP is

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

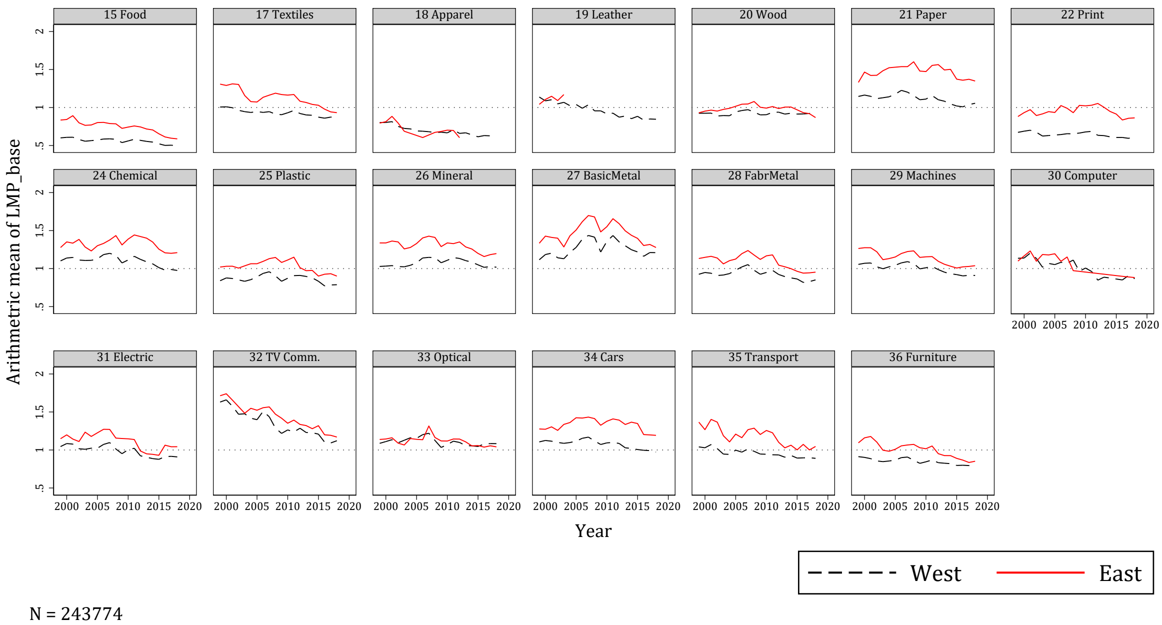
on a similar level in both regions, e.g. in the *apparel* industry or the *computer* industry. Similarly, Figure 3, Column 1 shows that there is a East German labor market power premium across all firm size-classes. Higher labor market power levels of East German firms as reported in Figure 1 are thus not an exclusive phenomenon of certain industries or firm types. Instead, this is a widespread feature across very different firm types in our data.

Fact 3: There are fewer large firms in East Germany. Figure Figure 4 displays the firm size distribution for East and West Germany for 1995 and 2015. East Germany is characterized by a greater prevalence of smaller firms and fewer large firms compared to the West. While the size distributions have converged to some extent over time, the relative scarcity of large firms in the East compared to the West remains a prominent feature of the distribution even in 2015, i.e., 25 years after German reunification. This is a well-established fact that is, for instance, in line with Bachmann et al. (2022). We can confirm this fact even within our sample of manufacturing firms with 20 or more employees.

Fact 4: East German firms are less innovative. Figure 5 compares the innovative activity of East- and West-German firms. We study averages of patents per employees and R&D expenditures per employees, which are measures of innovation outputs and inputs, respectively. Along both dimensions, we find that East German firms lack behind their Western counterparts, which is consistent with the productivity differences reported in Figure 1. The gap in innovative activity is persistent and even widens over time.

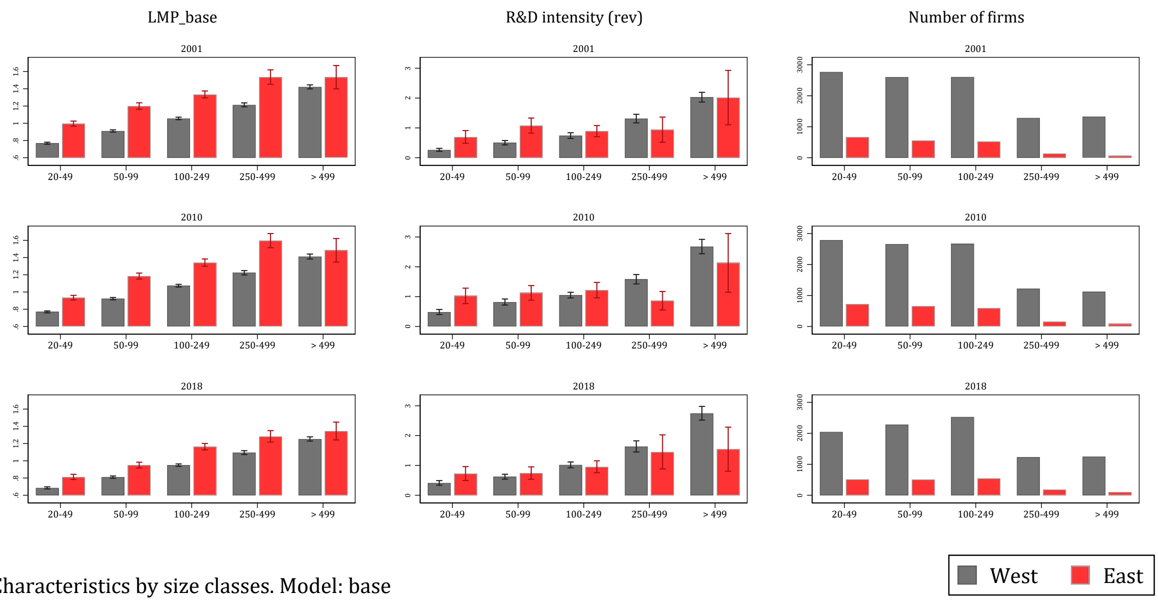
Fact 5: Firms with higher labor market power innovate less. Table 2 presents our core empirical result. The table displays a set of regression results from projecting firms' R&D intensity of firms' labor market power and a set of other variables, while controlling for industry and year fixed effects. 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

Figure 2: Labor market power, across industries and time



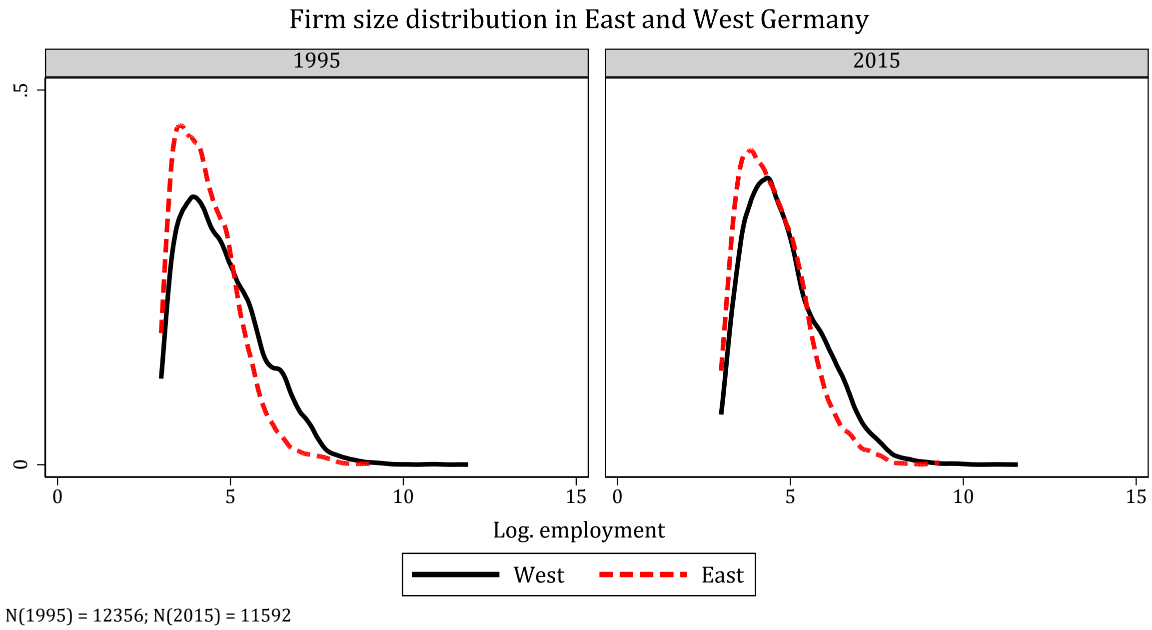
Notes: This plot shows the levels of LMP over time for East and West Germany across the industries (2-digit WZ2002) in our sample. With the exception of the Apparel, Optical and Computer sectors, LMP in the East is consistently and in most cases sizably higher than in West Germany. Industry composition is therefore not driving our main results. *Source*: AFiD, own calculations

Figure 3: LMP and R&D intensity, by size class



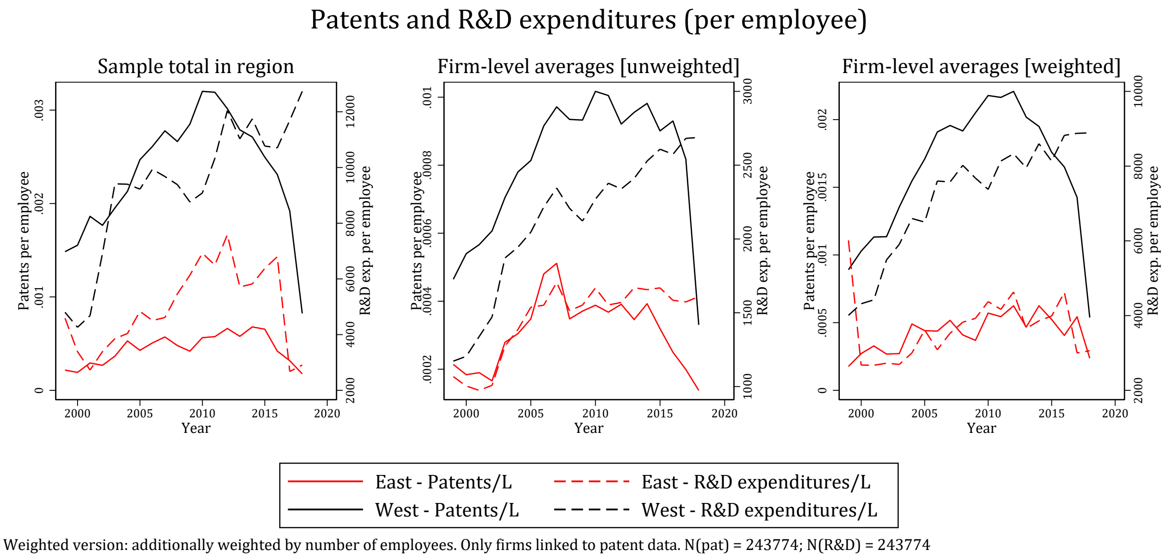
Notes: This bar plot shows for different firm size classes the avg. labor market power (first column), which is generally higher in the East, and R&D intensity (second column), which is higher (lower) for smaller (larger) firm in East Germany compared to West Germany. This can be seen for the years 2001, 2010 and 2018 (rows). In the third column it also shows the number of firms in each size-class, exhibiting fewer large firms in East Germany. *Source*: AFiD, own calculations

Figure 4: Firm size distribution, 1995 - 2015



Notes: Density plot showing the firm size distributions of East and West Germany, measured as the log number of employees (in headcounts). It shows that the firm size distribution in East Germany is consistently and persistently smaller in East Germany compared to the West. *Source*: AFiD, own calculations

Figure 5: Patenting and R&D expenditures, across East-West-Germany



Notes: Plots show patents and R&D expenditures per worker, respectively for East and West Germany over time. The first panel shows the sample totals per regions, the second panel shows unweighted firm-level averages and the third shows firm-level averages weighted by sales volume. The innovation gap appears smaller in the middle picture because small Eastern firms innovate more than Western firms, but when considering totals or weighting by sales volume, i.e. aggregate importance of firms, the innovation gap for both measures is very large. *Source*: AFiD, PATSTAT (via AMADEUS), own calculations

Table 2: Correlation of R&D intensity and LMP; source: AFiD, own calculations

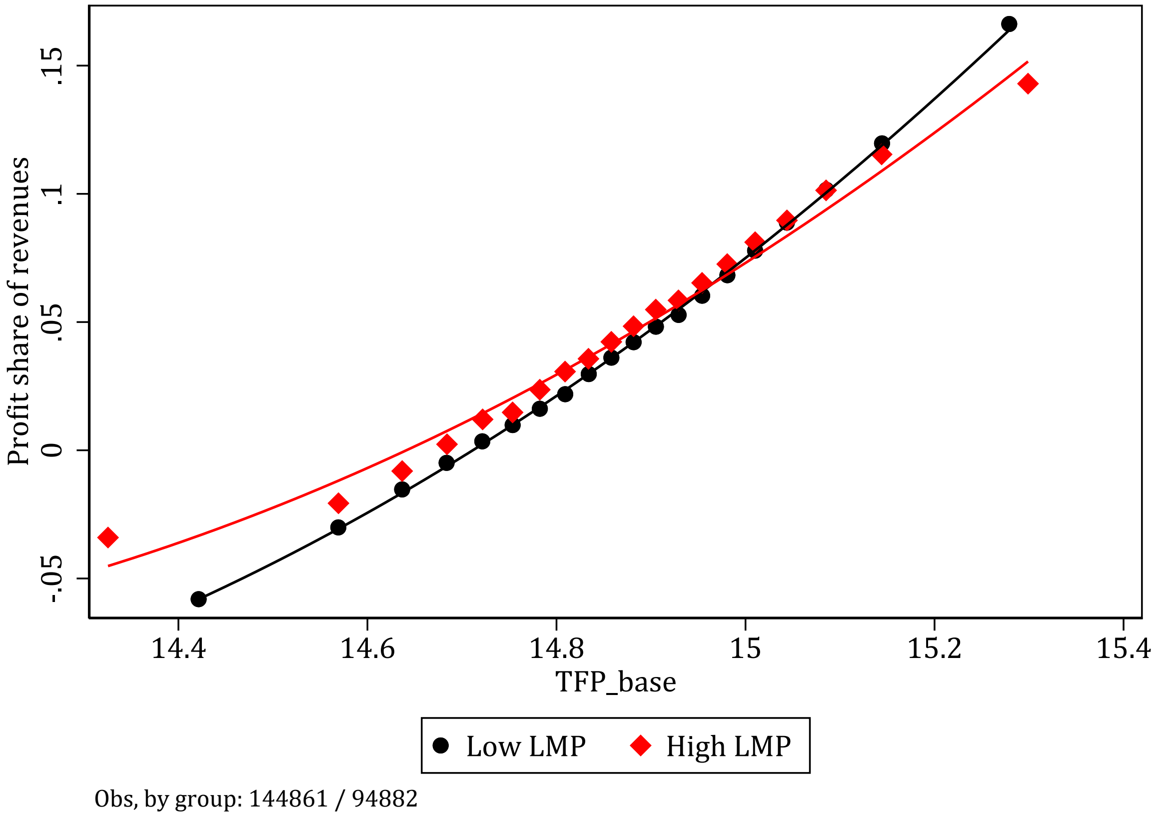
VARIABLES	(1) R&D/sales	(2) R&D/sales	(3) R&D/sales	(4) R&D/sales	(5) R&D/sales
Labor market power		-0.00783***	-0.00655***	-0.00887***	-0.00830***
		(0.000478)	(0.000447)	(0.000507)	(0.000531)
East = 1				0.00411***	0.00438***
				(0.000433)	(0.000453)
East = 1 # LMP_base					-0.00240***
					(0.000786)
l	0.00258***	0.00246***	0.000786**	0.00284***	0.00278***
	(0.000243)	(0.000240)	(0.000387)	(0.000244)	(0.000245)
k	0.00214***	0.00339***	0.00220***	0.00338***	0.00338***
	(0.000158)	(0.000182)	(0.000371)	(0.000182)	(0.000182)
Constant	-0.0370***	-0.0482***	-0.0228***	-0.0494***	-0.0497***
	(0.00195)	(0.00217)	(0.00588)	(0.00218)	(0.00217)
Observations	217,883	217,883	217,884	217,883	217,883
R-squared	0.206	0.214	0.009	0.217	0.217
Industry4d FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	No	No
Firms	38878	38878	38878	38878	38878

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

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.

Fact 6: 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 3, Column 2 reveals interesting heterogeneities with respect to R&D investment across firm sizes. This part of the figure reports average R&D intensities

Figure 6: Productivity and profits under different LMP regimes, source: AFiD, own calculations



Notes: Binscatter plot with fitted quadratic regression lines of profit share in revenues (with profits equal to revenues minus labor, material and capital costs) on TFPQ, separately for firms with high LMP ($LMP > 1$) or low LMP ($LMP \leq 1$). *Source*: AFiD, own calculations

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.

Fact 7: 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 6 show binned scatter plots from projecting profit shares in sales against productivity levels for firms with high and low labor market power levels. We define profits as sales revenues minus costs for labor, materials, and capital. Then, we split firms according to our LMP measure at a value of one, which refers to the competitive labor market level. As discussed, values below unity could be rationalized by worker-side labor market power. Hence, firms with high LMP are firms with market power over workers and low LMP firms are firms that pay wage equal or higher than their MRPL.

As expected, firms with higher productivity levels generate greater profits. However, this relationship is 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 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.

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. Profit increases from TFP improvements are declining in firms' labor market power.

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 prevalence of LMP in the East, the lack of innovation and TFP growth, and the simultaneous persistence of both effects is striking. The mechanism that we have in mind is that the expected profits from labor market power initially icentivize firms to reach a certain size threshold at which firms can exploit workers. Yet, once they grow too big, 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 in an increasing supply curve. In the next section we develop a model that elucidates this mechanism through which LMP can influence firms' innovation decisions in a standard theoretical framework.

4 Theoretical model

In this section, we develop a simple static model that captures the mechanism through which LMP lowers the incentives to innovate. Compared to the more intricate empirical model we use to estimate productivity and labor market, this is a simplified version with only one production input, labor, which is sourced from a non-competitive market. The firm acts as a price-setter on the labor market, which itself is characterized by an increasing labor supply curve. Our model will capture the key mechanisms highlighting how labor market power affects innovation incentives. While we keep the model simple for tractability, our main insights will also hold in more general scenarios with multiple production inputs as long as inputs are no perfect substitutes for labor. For now, our static model only speaks to productivity improvements in existing product lines of firms, i.e., only internal innovation. However, the key mechanism can also 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. This is because labor market power generally reduces the incentives of firms to grow, which creating a trade-off between the returns from innovation/increasing firm size and the returns from monopsonstic exploitation (i.e., staying smaller than optimal to mark down wages).

4.1 Demand structure

Each firm produces a single intermediate good j monopolistically. All intermediate goods in the economy are of mass one and are aggregated following Dixit-Stiglitz (1977) with constant elasticity of substitution:

$$Y_t = \left[\int_0^1 x_j^{\frac{\sigma-1}{\sigma}} \, dj\right]^{\frac{\sigma}{\sigma-1}} \tag{5}$$

Aggregate output is used for consumption in the standard fashion, i.e., $Y_t = C_t$. For the following static mode, we suppress the time subscript t. The final good producer maximizes the following problem:

$$\max_{x_j} \Pi = \left[\int_0^1 x_j^{\frac{\sigma-1}{\sigma}} \, dj\right]^{\frac{\sigma}{\sigma-1}} - \int_0^1 p_j x_j dj \tag{6}$$

The first-order condition of this maximization results in the price for each intermediate good (with aggregate demand shifter Y, which we can - in the static world - normalize to 1):

$$p_j = \left(\frac{Y}{x_j}\right)^{\frac{1}{\sigma}} = \left(\frac{1}{x_j}\right)^{\frac{1}{\sigma}} \tag{7}$$

This demand structure features output market power and enables firms to operate at a profit even in an otherwise competitive economy. However, in the following we are also characterizing this scenario with input market power on the labor market.

4.2 Profit maximization with labor market power

Firms produce output, x_j, of intermediate goods j and anticipate the demand for their output, such that they maximize profits, π_{jt}, using a production function, $Q(L_{jt}, A_{jt})$, and paying wages, $w(L_{jt})$. Labor is the only production input and firms have price- and wage-setting power in output and labor markets. Output prices ensure a constant markup over marginal costs, as implied by p_{jt} from Eq. (7). Wages, $w(L)$, are a function of labor quantities. Profits can be written as:

$$\pi_{jt} = p_{jt} Q_{jt}(L_{jt}, A_{jt}) - w(L_{jt}) L_{jt}. \tag{8}$$

We specify the production function of each good x_{jt} in the following way:

$$x_j = Q_{jt}(L_{jt}, A_{jt}) = A_{jt} \cdot L_{jt}^{\alpha}, \tag{9}$$

where A_{jt} denotes hicks-neutral productivity and $0 < \alpha \leq 1$, i.e., there are weakly decreasing returns to scale.

Labor markets feature an upward-sloping labor supply given by:

$$w_{it}(L_{it}) = \beta L_{it}^{\varepsilon_{it}}. \tag{10}$$

This general functional form can nest a variety of labor market settings with increasing labor supply curves. For instance, in Bachmann et al. (2022), wages are specified as $w(L) = W\left(\frac{L}{S_r^L}\right)^{\varepsilon_r}$ and depend on the regional labor supply, S_r^L, regional supply elasticity, ε_r, and a parameter for the competitive wage, W (r denotes regions). The key point is that firms labor market power will increase in the elasticity of the labor supply curve, ε_{it}. In competitive labor markets, $\varepsilon_{it} = 0$.

Defining $\eta = \frac{\sigma-1}{\sigma}$ with $0 < \eta < 1$ and inserting Equation (9)and Equation (10) into the profit function in Equation (8) yields intermediate producer's static maximization problem:

$$\max_{L_{jt}} \pi_{jt} = \left[A_{jt} L_{jt}^{\alpha}\right]^{\eta} - \beta L_{jt}^{(1+\varepsilon_{it})} \tag{11}$$

The first-order condition for labor yields the following expression for firms' labor demand:

$$\frac{\partial \pi_{jt}}{\partial L_{jt}} \stackrel{!}{=} 0 \Leftrightarrow L_{jt}^{*} = \left[\frac{\alpha \eta A_{jt}^{\eta}}{\beta(1+\varepsilon_{it})}\right]^{\frac{1}{\varepsilon_{it}+1-\alpha\eta}}. \tag{12}$$

Note that $\frac{\partial L_{jt}^{*}}{\partial \varepsilon_{it}}$. Hence for a given productivity level, A_{jt}, firms are smaller than on competitive labor markets ($\varepsilon_{it} = 0$). We can relate Equation (3) also to our empirical measure of labor market power in Equation (3). To see this, note that as the wage is given by $w_{it} = \beta L_{it}^{\varepsilon}$ and firms' marginal revenue product is defined as $MRPL_{it} = \alpha \eta A_{jt}^{\eta}$, it holds that $\frac{MRPL_{it}}{w_{it}} = (1+\varepsilon_{it}) = \gamma_{it}$, which is our labor market power definition from our empirical analysis. Hence, despite our theoretical model is a simplified version of our empirical approach, $(1+\varepsilon_{it})$

perfectly captures our empirical labor market power measure. Therefore, letting ε_{it} vary regionally will allow us to capture the observed labor market power differences between East and West Germany even with this simplified static framework.

Finally, substituting L^*_{jt} back into the profit function yields profits in terms of parameters:

$$\pi_{jt} = \left[\left(\frac{\alpha\eta}{\beta(1+\varepsilon)} \right)^{\frac{\alpha\eta}{\varepsilon+1-\alpha\eta}} - \beta \left(\frac{\alpha\eta}{\beta(1+\varepsilon)} \right)^{\frac{1+\varepsilon}{\varepsilon-\alpha\eta+1}} \right] A_{jt}^{\frac{\eta(\varepsilon+1)}{\varepsilon+1-\alpha\eta}} \tag{13}$$

4.3 Returns to increasing productivity

So far the problem was stated such that the firm chooses its optimal amount of labor for a given productivity level, A_{it}. However, our main mechanism, as highlighted in the empirical section, postulates that LMP reduces not only current labor demand, but also disincentivizes innovation or firm growth. Through the lens of our model, innovation can be viewed as a costly decision to increase A_{it} from one period to the next. Firms will only conduct innovation if the returns, i.e., the added profit from increasing A_{it} minus the costs of innovation are positive. While our current framework does not specify innovation costs, we can study the derivative of the profit function in Eq. (13) to A_{it}, which defines the increase in profits from increasing productivity:

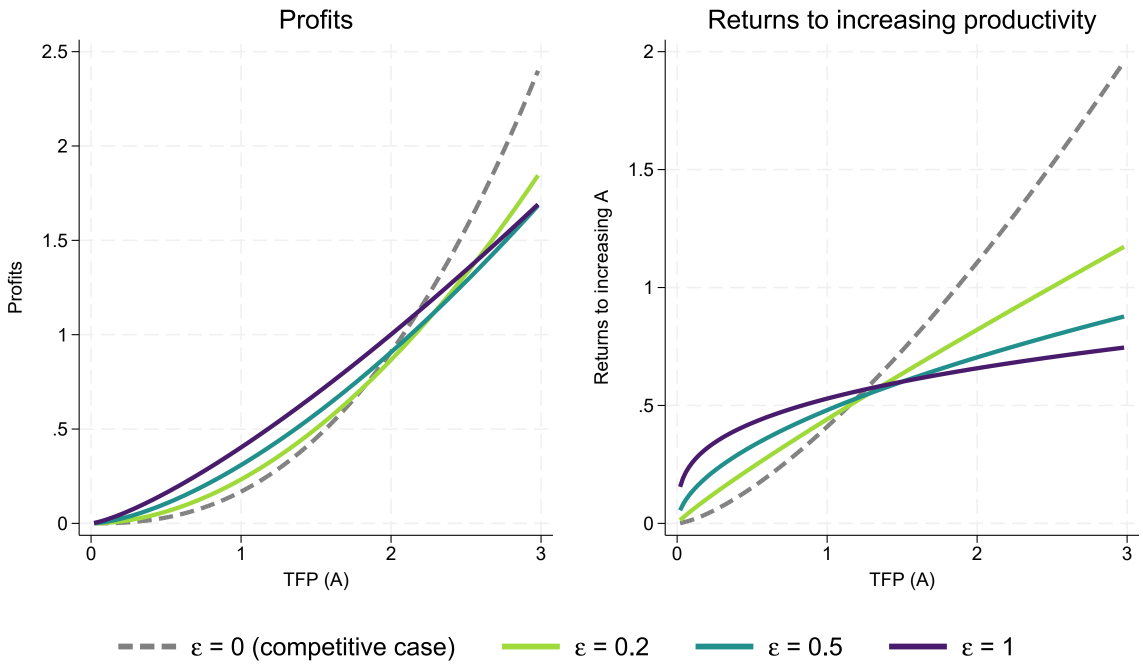
$$\frac{\partial \pi^*_{jt}(A)}{\partial A} = \left[\left(\frac{\alpha\eta}{\beta(1+\varepsilon)} \right)^{\frac{\alpha\eta}{\varepsilon+1-\alpha\eta}} - \beta \left(\frac{\alpha\eta}{\beta(1+\varepsilon)} \right)^{\frac{1+\varepsilon}{\varepsilon-\alpha\eta+1}} \right] \frac{\eta(\varepsilon+1)}{\varepsilon+1-\alpha\eta} A_{jt}^{\frac{(\eta-1)(\varepsilon+1)+\alpha\eta}{\varepsilon+1-\alpha\eta}} \tag{14}$$

Note that Eq. (14) depends on η, i.e., the firm's markup, the productivity, A_{it}, and the firm's labor market power, measured by ε_{it}. It turns out that while labor market power raises high profits, it imposes an optimal productivity level (or growth path) that is lower compared to the competitive equilibrium. Put differently: There is discrepancy between increasing profits through higher productivity and firm size and staying smaller than on competitive markets to mark down wages. As a result, there is a region where high labor market power firms are generally more profitable, but this advantage decreases in productivity and, as a direct corollary, in firm size. It turns out that the slope of productivity improvements, i.e., the value of Eq. (14) decreases faster the higher the firm's labor market power.

Figure 7 illustrates this mechanism by simulating our static model for different values of firms' labor market power (ε_{it}). The left panel projects profits against productivity. As shown, the higher firms' labor market power, the higher firms' profits at low productivity levels. However, above a certain productivity (size) threshold, profits become relatively smaller with higher levels of firm labor market power. Strinkingly, our graphical illustration can closely reproduce Figure 6, i.e., our empirical fact 7.

The right panel studies the profit gains from *increasing* productivity as a function of firms'

Figure 7: Labor market power and firm profits, depending on productivity level



Notes: Illustration of main mechanism: The left panel shows productivity (A) on the x-axis, profits on the y-axis and their relation in Eq. (13). In the right panel, the y-axis shows the returns to increasing A instead and shows the derivative of the profit function, i.e. Eq. (14). Profits are higher for firms with LMP (where $\varepsilon > 0$), but only up to a threshold value of A, depending on the value of ε. Afterwards returns are lower as firm expansion starts to cannibalize more on its labor market power. The returns to increasing A in the right panel show this flattening relationship explicitly. Parameter values: $\alpha = 0.7$, $\beta = 1$, $\eta = 0.9$;
Source: Own calculations

productivity level for different labor market power levels. This is effectively a dynamic version of the left panel in Figure 6. Our analysis shows that returns to innovation/increasing productivity are higher for high labor market power firms with low productivity. This is consistent with our empirical fact 6, i.e., that East-German firms, which have relatively high labor market power, invest more into R&D than their West-German counterparts.

However, these initial profit gains from increasing productivity quickly diminish. Beyond a certain productivity threshold, firms low (or without) labor market power have significantly higher incentives to increase productivity. Note that even with relatively modest levels of firm labor market power, the disincentives to invest in productivity growth, compared to the competitive benchmark, can be significant for high-productivity firms.

Notably, in our current framework, we have not yet introduced innovation costs. Clearly, if innovation was costly (or if innovation costs increase with higher productivity levels), it could become entirely unprofitable, depending on the specific shape of the cost function.[5] Nonetheless, even if firms simply grow at a smaller rate due to having high labor market power, the empirical dynamics the we observe, in particular the TFP and labor market power gaps between East and West Germany, can be qualitatively well explained by our mechanism.

[5] Increasing innovation costs at higher technology levels have been documented in various areas. See Bloom et al. (2020).

4.4 Dynamic incentives to innovate - very preliminary

So far, we have developed a framework within a simple static model from which we have drawn dynamic conclusions regarding the incentive to innovate and to grow. In this section, we will take this intuition to the data and estimate gains from innovation by iterating a simplified intertemporal value function on discretized data points along our dimensions of interest. We use this framework to estimate how firm profits react to firms' position in a discretized type space. Using this approach, we compare East to West Germany with the documented labor market power differences as our motivating fact.

To keep the problem computationally tractable in the actual estimation, we bin several relevant variables (productivity, research intensity, labor output elasticities) and define a type θ as a combination of these characteristics. This allows us to express a firm's value, i.e. its expected profits, in discrete time, as:

$$V^f(\theta_t) = \pi(\theta_t) + \beta \sum_{x=1}^{X} p(\theta_{t+1} = x|\theta_t) \cdot [V^f(\theta_{t+1}) - V^f(\theta_t)] \tag{15}$$

Where $\pi(\theta_t)$ are current profits, β is the discounting factor and θ_{t+1} indexes the possible types next period: $p(\theta_{t+1}|\theta) \cdot [V_t^f(\theta_{t+1}) - V_t^f(\theta)]$ denotes the value gain for the firm if its next-period type were θ_{t+1}, times the realization probability of this event. The firm's only decision in this notation is to pick its current type θ. While the firm cannot *directly* chose its productivity, labor market power (i.e. location) or its labor production function coefficient and so cannot choose freely among all of its characteristics, it can choose whether to do R&D, which is the case we focus on in this exercise. The optimal type to pick depends on the change in $p(n|\theta)$ for any level of R&D spending - and the transition probabilities from that future type. Using this notation of the problem, allows us to remain agnostic about the causes for labor market power or the functional forms of any of the relevant variables. Indeed, assumptions about these objects are not necessary to solve the problem numerically.

Empirically, we define 36 types as the intersections of three TFP levels (firms with less than 90% of sector level TFP, firms with more than 110% and those in the middle), three levels for the output elasticity of labor α (firms with less than 90% of sector level α, firms with more than 110% and those in the middle), two R&D levels (firms with and without R&D expenditures) and firms in East and West Germany (and thus with high and low average labor market power). The resulting 36 types are all filled with between 439 and 2614 firm observations, which allows us to measure the characteristics of firms in these groups with reasonable accuracy. This is especially pertinent for the Transition matrix between the types $p(\theta_{t+1} = x|\theta_t)$. Thus, $\pi(\theta)$ and $p(n|\theta)$ can be estimated by their sample analogues. In particular, we measure the profits and the profit gains upon transition for each of these type groups.

The transition matrix between the different bins has a high degree of stability, which is in line with previous work (Peters et al., 2017): R&D performing firms have a higher than 90% chance to continue with R&D, while non-R&D firms have a less than 10% chance to start. Likewise, firms have a 85% chance to stay in their labor elasticity bin and a 75% chance to stay in their productivity bin. R&D mainly increases the chance to exit the lowest productivity bin, while the effects for higher productivity firms are much less clear and depend on the type.

Estimating firm value instead of static profits from Eq. (15) requires contraction mapping following Peters et al. (2017). This numerical technique solves the simultaneous equation problem in Eq. (15) accounting for the fact that the firm value given any type θ contains itself and all other types.

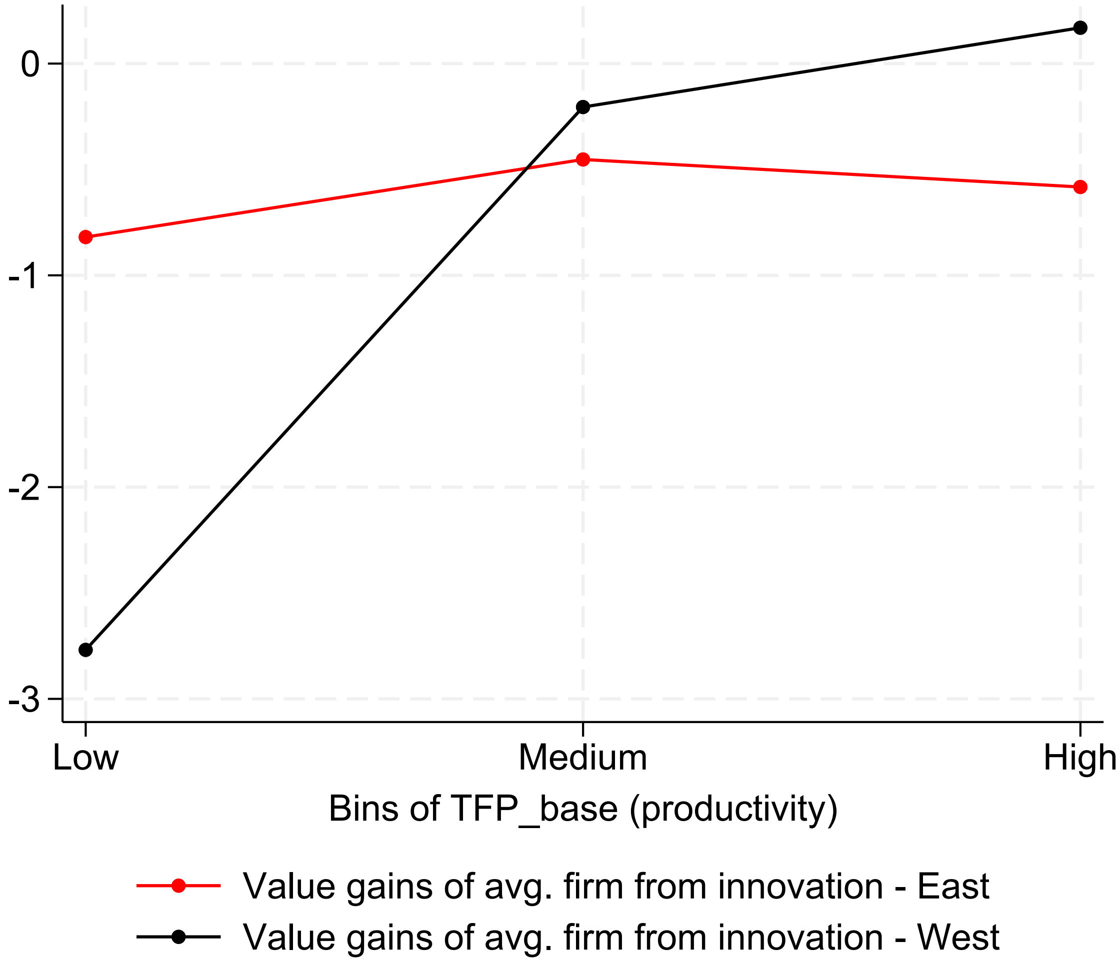
Figure 8 depicts the value of starting R&D for the average firm for East and West German firms, where we view East German firms as high and West German firms as low labor market power firms across the TFP distribution. This expected average value does not only include the direct profit increase, but also the additional value gains from improving the position of the firm due to future R&D. Consistent with our previous analysis, the returns to innovation are lower in East Germany (i.e., high labor market power firms), by 0.3 to 0.7 million Euro, except for low productivity firms, where returns actually exceed the Western ones by more than 1.5 million Euro, according to this. This is in line with comparative theoretical analysis in Figure 7 and our empirical findings in Figure 6. The flatter relationship between profits and productivity disincentivizes further R&D among East-German firms relative to West-German firms. Note that according to Figure 8 small/low-productivity East German firms are actually more likely to invest into R&D than their West-German counterparts (empirical fact 6), while the relationship reverses for large firms, which results in overall less R&D in East Germany (empirical fact 4) and fewer large firms (empirical fact 3).[6]

4.5 Future work

In future revisions of this paper, we plan to develop the static model from Section 4 into a full dynamic general equilibrium (DGE) growth model with an endogenous, costly innovation process. This will also allow us to precisely quantify the contribution of the LMP effect to the overall TFP gap in Germany. The mechanism laid out in this static framework is the core mechanism that will lead to different growth outcomes in such a model. With research costs making the returns laid out in 14 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 Section 4.4. 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 (Equation (12)), our model clearly generates smaller firms sizes under LMP than in the competitive labor market. Fact 3 documented this empirically,

[6]These results are very preliminary and subject to change. In particular, we need to repeat this analysis and explicitly account for LMP differences within East and West Germany.

Figure 8: *Effect of R&D on Firm Value*



Notes: The figure describes the computed firm value increase from R&D for the average firm in East and West Germany (in Millions of €) at different TFP levels. It is often negative, but the average firm does not conduct R&D. The firms that actually do receive positive shocks (i.e. pay less than the average cost of R&D) as in (Peters et al., 2017). Returns to R&D in East Germany are lower except for very low productivity levels.
Sources: AFiD; own computations.

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 7. 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 Table 2 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 Table 2. 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.[7] 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.[8]

Using the CompNet data, Figure 9 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.[9]. We categorize value-added per worker and average labor market power in terms of within-

[7]For details on the CompNet data, please see CompNet (2023).
[8]The data is based on firm-level data and regional values are assigned based on headquarters.
[9]Unfortunately, the CompNet data does not include NUTS2 information for Germany.

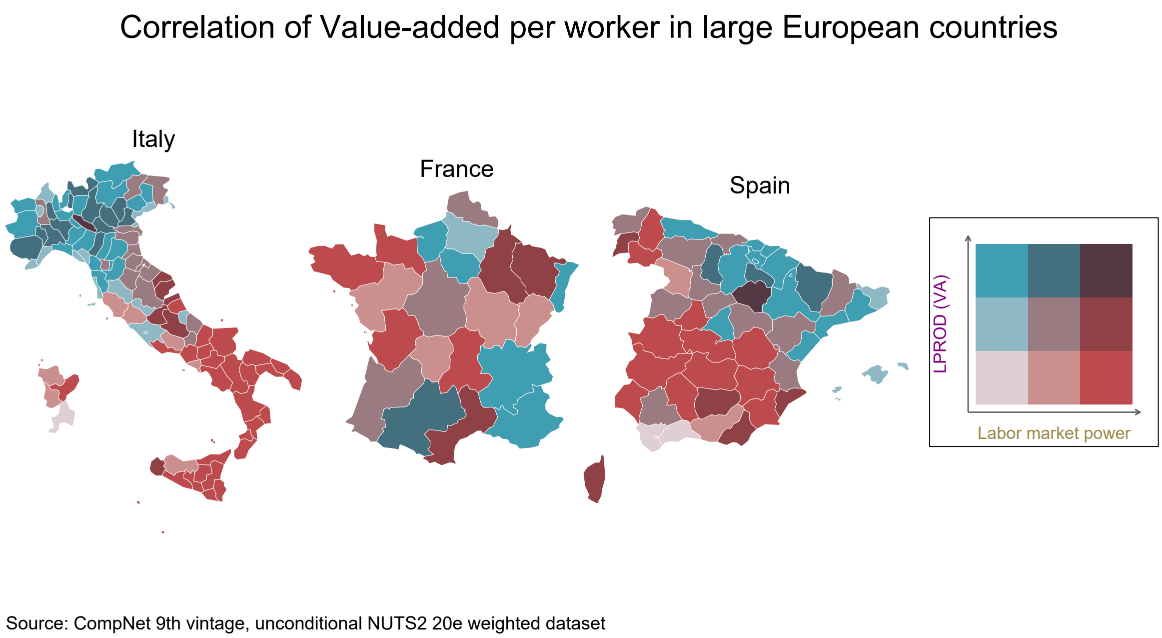


Figure 9: Labor market power and labor productivity in large European countries

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 10 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-document negative effect on wages and overall production output, we develop a framework in which labor market power can dynamically influence firm 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

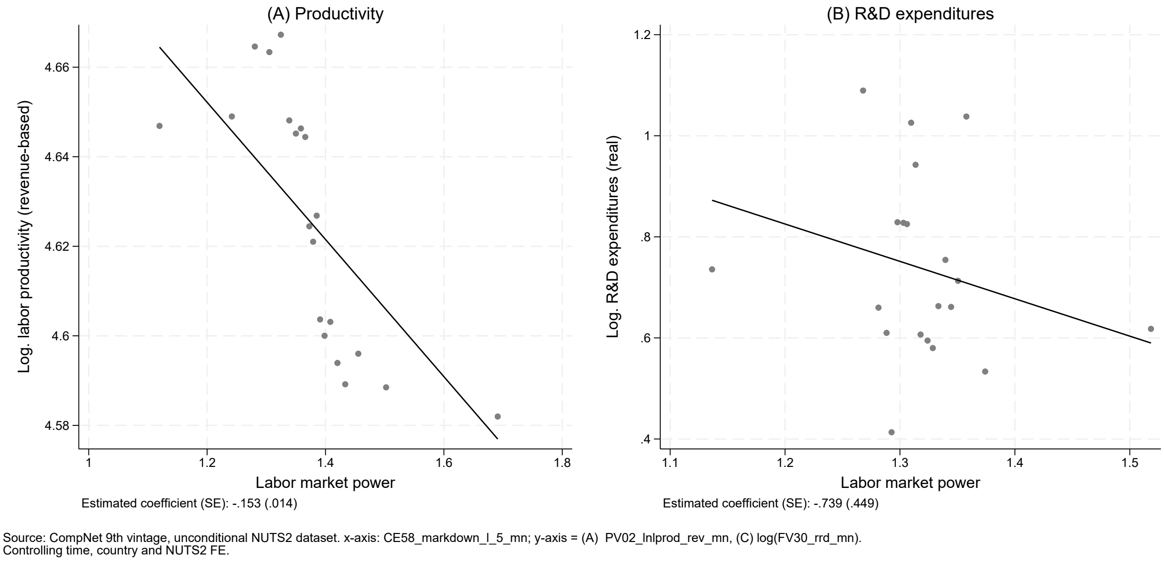


Figure 10: Labor market power, productivity and R&D across regions in 19 European countries

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 investment of firms, we use rich German manufacturing-sector firm-level panel data that allows us measure firms R&D activity and to estimate start-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 incentive 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.

Combining our model with the data, we estimate that East-German firms, who have much higher labor market power than West-German firms, gains from innovating, are, on average, between 0.3 and 0.7 Million Euro lower compared to their Western counterparts. Strikingly, this relationship is reversed for low-productivity small firms: Low-productivity East German firms gain about 1.5 Million Euro more, because innovation allows these firms to grow to a moderate size and profit from the high labor market power environment. This result confirms our proposed relationship between labor market power and R&D investment.

While we focus on the German case, additional European evidence from the CompNet dataset shows that labor market power is negatively associated to 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 patents, which we have linked to firm dataset, 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 to 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: Main sample: Descriptives for East and West Germany, 1999-2016, source: AFiD

East	Sample Period	Variable	Mean	SD	Median	Sample share	N
0	1999 - 2016	L	308.09	2207.06	100.00	0.84	182159
0	1999 - 2016	LMP_base	1.00	0.43	0.92	0.84	182159
0	1999 - 2016	TFP_base	13.27	3.15	14.69	0.84	182159
0	1999 - 2016	Nom. R&D intensity (VA)	1.00	2.67	0.00	0.84	182159
1	1999 - 2016	L	145.77	375.16	73.00	0.16	35724
1	1999 - 2016	LMP_base	1.16	0.49	1.06	0.16	35724
1	1999 - 2016	TFP_base	13.12	3.20	14.53	0.16	35724
1	1999 - 2016	Nom. R&D intensity (VA)	1.04	3.25	0.00	0.16	35724

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 Appendix B.1.2, 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: $\lambda_{it} = MC_{it} = \frac{P_{it}}{\mu_{it}}$. Expanding Equation (B2) with $\frac{M_{it}}{Q_{it}}\frac{Q_{it}}{M_{it}}$ and using the definition of the output elasticity for intermediate inputs, $\theta^M_{it} = \frac{\partial Q_{it}}{\partial M_{it}}\frac{M_{it}}{Q_{it}}$, yields an expression for the firm's markup (μ_{it}):

$$\mu_{it} = \frac{P_{it}}{MC_{it}} = \theta^M_{it}\frac{P_{it}Q_{it}}{z_{it}M_{it}}, \tag{B3}$$

The first order condition with respect to labor is:

$$w_{it}\left(1 + \frac{\partial w_{it}}{\partial L_{it}}\frac{L_{it}}{w_{it}}\right) = \lambda_{it}\frac{\partial Q_{it}}{\partial L_{it}} = MRPL_{it}. \tag{B4}$$

$\frac{\partial w_{it}}{\partial L_{it}}\frac{L_{it}}{w_{it}} = \frac{1}{\epsilon^L_{it}}$ is the inverse labor supply elasticity. Expanding Equation (B4) with $\frac{L_{it}}{Q_{it}}\frac{Q_{it}}{L_{it}}$ and inserting Equation (B2) yields the wage markdown expression from the main text:

$$\gamma_{it} = \left(1 + \frac{\partial w_{it}}{\partial L_{it}}\frac{L_{it}}{w_{it}}\right) = \frac{\theta^L_{it}}{\theta^M_{it}}\frac{z_{it}M_{it}}{w_{it}L_{it}}, \tag{B5}$$

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

B.1.2 Alternative setting: Bargaining model

So far, we focused on a case where firms exert monopsony power. However, a large literature has highlighted that also workers possess labor market power, which can also drive a wedge between wages and marginal revenue products (e.g., **?**, **?**, Caselli et al. (2021), **?**), for instance, if firms share product market rents. We now derive a standard rent-sharing model and show that allowing for worker-side labor market power does not affect our empirical labor market power measure. In fact, the presence of worker-side labor market power can rationalize why we (and most other studies) find a significant portion of workers receiving wages above marginal revenue products. Consider that employees maximize utility:

$$U(w_{it}, L_{it}) = w_{it} L_{it} + (\overline{L}_{it} - L_{it})\overline{w}_{it}. \tag{B6}$$

$\overline{w}_{it} \leq w_{it}$ is the reservation wage. $\overline{L}_{it}$ is the competitive employment level. Firms produce output using the production function of the main text, $Q_{it} = Q_{it}(.) = F(L_{it}, K_{it}, M_{it})\Omega_{it}$. Firms and workers bargain over wages and employment and solve the following Nash-bargaining problem:

$$\max_{w_{it}, L_{it}, M_{it}, K_{it}} (\zeta_{it} log(L_{it}(w_{it} - \overline{w}_{it})) + (1 - \zeta_{it}) log(P_{it} Q_{it} - w_{it} L_{it} - z_{it} M_{it} - r_{it} K_{it}), \tag{B7}$$

where $\zeta_{it} \in [0, 1]$ denotes worker's bargaining power.[10] Note that in the event of a breakdown of negotiations, workers' outside option is the reservation wage, whereas a firm's outside option is the zero-profit outcome. The latter follows the literature and simplifies derivations; it is, however, not essential for our conclusions (e.g., **?**). The first order condition with respect to intermediate inputs yields the same markup expression as in Appendix B.1.1:

$$z_{it} = \frac{P_{it}}{\mu_{it}} \frac{\partial Q_{it}}{\partial M_{it}} \rightarrow \mu_{it} = \theta^M_{it} \frac{P_{it} Q_{it}}{z_{it} M_{it}}. \tag{B8}$$

The first order condition with respect to labor implies:

$$w_{it} \left(1 - \frac{\zeta_{it}}{1 - \zeta_{it}} \frac{P_{it} Q_{it} - w_{it} L_{it} - z_{it} M_{it} - r_{it} K_{it}}{w_{it} L_{it}}\right) = MRPL_{it}, \tag{B9}$$

where $MRPL_{it}$ denotes the marginal revenue product of labor. Combining Equation (B8) with Equation (B9) yields the same equation for the wage markdown as in the main text:

$$\gamma_{it} = \left(1 - \frac{\zeta_{it}}{1 - \zeta_{it}} \frac{P_{it} Q_{it} - w_{it} L_{it} - z_{it} M_{it} - r_{it} K_{it}}{w_{it} L_{it}}\right) = \frac{\theta^L_{it}}{\theta^M_{it}} \frac{z_{it} M_{it}}{w_{it} L_{it}}, \tag{B10}$$

where we used $MRPL_{it} = \frac{P_{it}}{\mu_{it}} \frac{\partial Q_{it}}{\partial L_{it}}$. Note that in this setting, $0 \leq \gamma_{it} \leq 1$, which helps explaining why the data features many firms where wages exceed marginal revenue products of labor.[11]

[10] We follow the literature and write the rent-sharing model in static terms.

[11] Mertens (2023) generalizes this setting to a case where firms have monopsony power over some workers while they bargain with other workers over rents. This more general model rationalizes why researchers typically simultaneously observe firms with wages above and below the marginal revenue product of labor. Even in such a more complex setting, our empirical labor market power measure remains valid.

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.[12] 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

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

prices. We use this price index to deflate observed firm revenue.[13] We construct firm-specific Törnqvist price indices for each firm's 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.[14] 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}.[15]

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

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

[14] 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.

[15] 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.

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

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

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

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

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

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

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

Identifying moments and results We estimate Eq. (C6) separately by two-digit NACE rev. 1.1 industries using a one-step estimator as in Wooldridge (2009).[16] Our estimator uses lagged values of flexible inputs (i.e., intermediates) as instruments for their contemporary values to address the dependence of firms' flexible input decisions on realizations of ξ^{tfp}_{it}. Similarly, we use lagged values of terms including firms' market share and output price index as instruments for their contemporary values.[17] Our identifying moments are:

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

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

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

where for convenience, we defined:

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

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

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

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

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

[16] 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).

[17] 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.