Labor market power and innovation

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Abstract:

We document that firms possess high labor market power (LMP) across structurally weak European regions. We study the effect of LMP on firms' innovation decisions and aggregate growth. Theoretically, LMP has a nonlinear relationship with RD: Higher profits incentivize entry and innovation of very small firms, but medium and large firms are disincentivized to innovate, since they have to pay higher wages if they grow further. To test this prediction empirically, we estimate LMP across German manufacturing firms and replicate the predicted innovation pattern. High and low LMP firms behave similarly after controlling for LMP. We build an endogenous growth model to understand the size of this effect relative to the overall innovation and productivity gap between East and West Germany

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

1 Introduction

Throughout the developed world, union membership is declining (Katz and Autor, 1999) and the labor share is falling (Barkai, 2020; De Loecker and Eeckhout, 2018; De Loecker et al., 2020). This is partly explained by substantial increases in firms' labor market power, especially after 2000: Firms' markdown increased from 1.1 to 1.6 in the US (Kirov and Traina, 2023; Yeh et al., 2022) and from 1.34 to 1.42 in German manufacturing (Mertens, 2022). Firms with high labor market power necessarily have to pay higher wages when they increase their size, which lowers aggregate productivity by 20% in the US (Berger et al., 2022) and 10% in Eastern Germany (Bachmann et al., 2022).

However, apart from static distortions that labor market power causes, there is also a dynamic implication: A large part of the gains from firm productivity growth come from increasing firm size and thus employment, which increases wages. Firms with high price setting power on the labor market are thus disincentivized from investing in productivity increases. We observe that throughout Europe, firms' labor market power is higher in less productive regions within countries and posit this stylized fact as an important obstacle to convergence within countries. We present micro evidence for this channel and incorporate it into an endogenous growth model to quantify its effect size. We find XXXXX.

On the firm level, we employ two independent empirical strategies: First, we use state of the art estimators for total factor productivity (TFP) and labor market power in our German manufacturing firm-level data, following Mertens (2022): This methodology builds on firm level production function estimation and measures the difference between the marginal revenue productivity of labor and the wage (which would be equal in the case of no labor market distortions).[1] The German micro data is ideally suited for this analysis as it contains firm-specific output prices and quantities, which allows us to address the "price-bias" when estimating production functions (De Loecker et al. (2016), Bond et al. (2021), De Ridder et al. (2024)). Second, we measure firms' labor supply elasticity directly, exploiting exogenous shocks to firms' labor demand and information on average wages. Specifically, we use changes in the demand for manufactured goods on the world market, which increases firms' labor demand depending on the goods they can manufacture. We then observe the resulting changes in wages. Both strategies yield broadly similar results, though we can only use exogenous trade shocks for the German part of our data. To directly study innovation outcomes associated with labor market power, we also merge the EPO patent data base to our German data.

To broaden our analysis, we also use European firm level data provided by the Competitiveness Research Network (CompNet). CompNet harmonizes European administrative data sets across 20 European countries and then runs identical data collection protocols on these data sets. Specifically, we use the XXXcitation needed data setXXXX, which reports the Mertens (2022) measure of firm labor market power and its correlates across XXXXX countries. In addition, we use the German underlying microdata, a comprehensive panel data set of German

[1] Estimating labor market power from production functions builds on Dobbelaere and Mairesse (2013) and has also been used in Yeh et al. (2022) and Caselli et al. (2021), among others.

manufacturing firms covering the years from 1995 to 2016.

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

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 in 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 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 invest relatively more in R&D than small West-German firms. However, for higher productivity levels, the relationship reverses. Large, highly productive firms are, relative to a competitive labor market scenario, discouraged from investing in 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 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).

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 7 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. Sectionsec:data describes our data sources. Section 4 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 6 derives our theoretical framework that describes the connection between labor market power, productivity, and R&D investment and estimates the value of innovation for different firms and their optimal strategies. Section 7 discusses robustness checks and the relevance of our analysis beyond the German context. Section 8 concludes.

2 Literature Overview

Our results add to the literature on non-convergence between countries, but are more pertinent on convergence within countries and especially East and West Germany (see Johnson and Papageorgiou (2020); Uhlig (2006) for surveys). We are not the only ones to propose labor market power as an important cause for the non-convergence. Bachmann et al. (2022) develop a similar argument but focus on how the labor supply elasticity affects firms' business models. In their paper, firms remain small if they face a steep labor supply curve to economize on low wages. Our paper, however, focuses on how the incentives of firms to invest into R&D and therefore their long-term growth perspectives are shaped by LMP. Moreover, we actually estimate labor market power and its effect on innovation in a microeconometric setting, which informs our modelling approach. We also provide evidence that the dampening effect of labor market power on innovation is not an exclusively East German phenomenon. In a planned extension of this paper, we also aim to show that the nature of our innovation mechanism leads to differences in firm dynamics across East and West Germany that exacerbate the lack of productivity convergence in Germany.

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

In estimating the detrimental effects of firms' market power, we connect to a large literature documenting and discussing the increase in firms' market power using production function estimation techniques (**?**De Loecker and Warzynski, 2012). However, this literature focuses on *product* market power, while we study the effects of rising *labor* market power. The effect of product market power on innovation is ambiguous because some product market power is necessary to incentivize firms to innovate (Aghion et al., 2005, 2006). At the same time, incumbents who already enjoy high markups due to past innovation generally have a lower incentive for innovation (cf. **?**). To our knowledge, we are the first to analyze the dynamic innovation incentives of firms with labor market power.

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

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

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

3 Data

3.1 CompNet: European data

We use the 9th vintage CompNet data (CompNet (2023)), which is a micro-aggregated database for 22 European countries. The data is collected and provided by the Competitiveness Research Network (CompNet). CompNet sources its data from representative administrative firm-level data located within European national statistical institutes and central banks. The CompNet team closely cooperates with the individual data providers and invests significant efforts in harmonizing the input data to maximize comparability across countries. Next, the CompNet team distributes identical data collection protocols (i.e., Stata codes) across the data providers to compute micro-aggregated results. From these results, the CompNet team constructs the CompNet database. The data is aggregated at various levels. We use the regional nuts2-level data, which is the most detailed geographic aggregation level available.

The data contain, among other features, information on firms' sales, inputs, expenditures, labor market power (wage markdowns), productivity, and research and development expenditures. Labor market power and total factor productivity measures are derived from a production function estimation algorithm that is similar to the one that we use in our German firm-level data and we detail the CompNet approach in Appendix XXXX. The key differences to our approach with German manufacturing data that we describe in Section 4.1 are i) that CompNet does not contain firm-specific price information and therefore uses market shares information to control for price biases in the production function, and ii) that CompNet uses a two-step control function approach as in Ackerberg et al. (2015), while we use a one-step control function approach similar to Wooldridge (2009).

The CompNet data cover the years 1999-2021 and the NACE rev. 2 industries 41-43 (construction), 45-47 (wholesale/retail trade and repair of motor vehicles and motorcycles), 49-53 (transportation/storage), 55-56 (accommodation/food services), 58-63 (information and communication technology), 68 (real estate), 69-75 (professional/scientific/technical activities), and 77-82 (administrative/support service activities). Yearly coverage varies across countries, and a few individual sectors are omitted in some countries (see Appendix Table XXXX).

We focus on the data containing firms with at least 20 employees as this is available for more countries and is consistent with our German micro data. To ensure representativeness, the data is weighted by firm population weights. For further details on the data, we refer to CompNet's User Guide (CompNet (2023)).

3.2 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.[2] The data is collected and provided by the German statistical offices and comprises all manufacturing firms with at least 20 employees. The data includes information on firms' employment, outputs, input expenditures, investment, including R&D expenditures, and, most notably, output sales, quantities, and prices of firms' individual products. While core variables, such as sales and employment, are available for the full population of firms with at least 20 employees, other variables are only available for a representative 40% sample, which is redrawn roughly every 4 years. We use this subset for our analysis, as it contains information on firms' R&D expenditures as well as variables that are required to estimate firms' labor market power. As capital stocks are not directly observed in the data, we use a perpetual inventory method following Bräuer et al. (2023) that derives capital stocks by accumulating observed information on investments and depreciations.

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

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

[3] Due to the high data quality, we clean our raw data with respect to outliers conservatively. We define the

3.3 EPO patent data

We augment this data further with an additional information source on firm-level innovation: patents. 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. Thus, we set the number of patents to 0 for unmatched firms in our sample.

4 Empirical Analysis

Neither labor market power nor R&D efforts are trivial to measure, especially on the firm level. In this section, we lay out our measurement strategy and its results. We use two different strategies on how to estimate labor market power. We then present evidence of the distribution of labor market power across the Regions of Europe and zoom in our special case (Germany), where the division between a less productive East and West Germany has persisted well past the communist period.

4.1 Jointly estimate labor market power and a firm production function

Labor market power. The key question in our study is how labor market power affects firms' incentives to invest into R&D. To derive a measure of firms' labor market power, we 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, 2021) **?**). 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

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.

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 rms. 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 $\frac{\partial P_{it}(Q_{it})Q_{it}}{\partial L_{it}}$.[4]

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.

[4] 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 6 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 (2021).

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 typically leads 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}).[5] 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).

5 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.

5.1 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

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

use the 9th vintage data from the Competitiveness Research Network (henceforth, CompNet data) at the NUTS2 and NUTS3 regional level.[6] 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.[7]

Using the CompNet data, Figure 1 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.[8]. We categorize value-added per worker and average labor market power in terms of within-country terciles. There is a clear negative correlation between the two variables, indicated by the colors on the diagonal between starkly blue and starkly red. In fact, almost all regions support the negative correlation between labor market power and labor productivity. Consequently, high firm labor market power is particularly prevalent in structurally weaker regions. Most notably, in Italy, where the North-South differences in economic development are similarly well-documented as in the German West-East case, the picture is closely in line with our descriptive results for Germany. We view this as strong out-of-context evidence supporting the validity of the mechanism we put forward in our paper.

To further highlight the relevance of labor market power in affecting productivity, Figure 2 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 4, 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.

Fact 1: East German firms are less productive and have higher labor market power. Figure 3 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

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

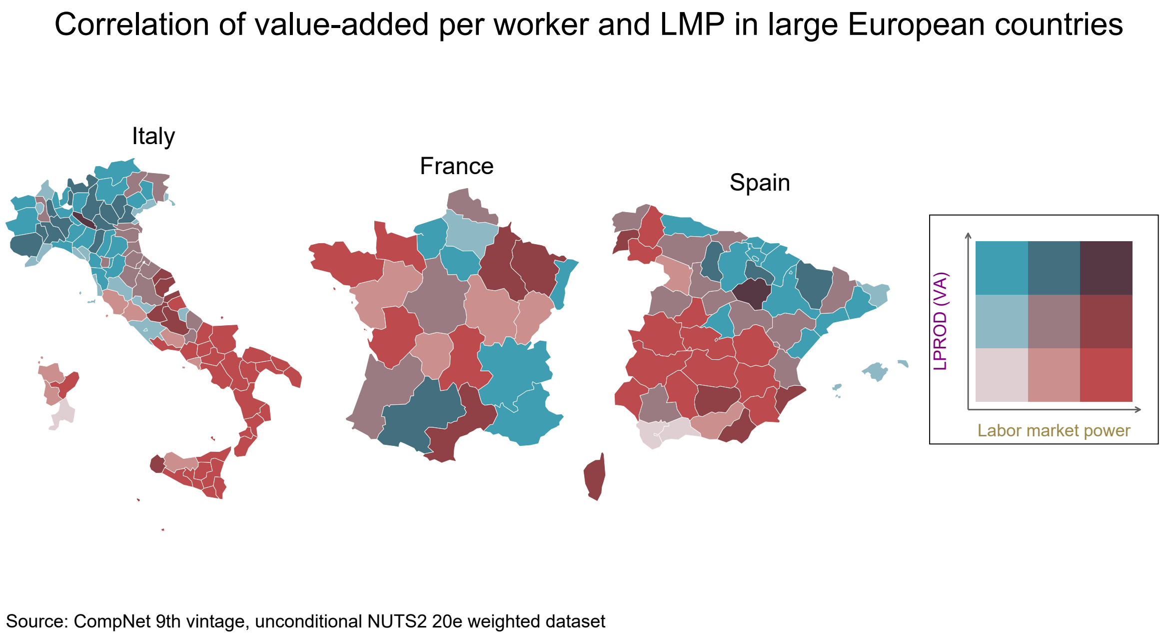


Figure 1: Labor market power and labor productivity in large European countries

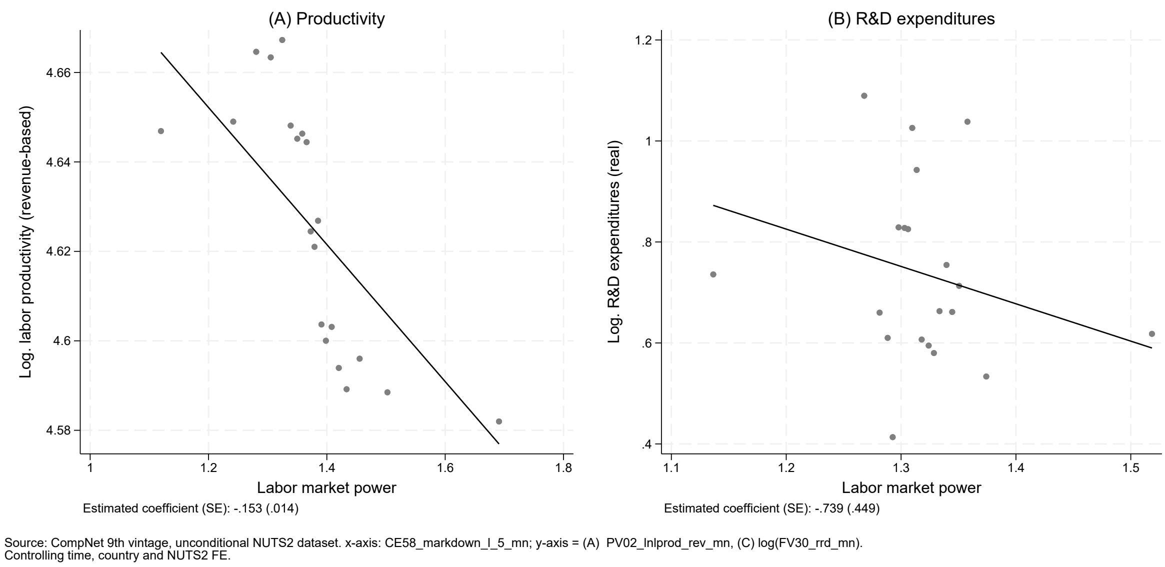
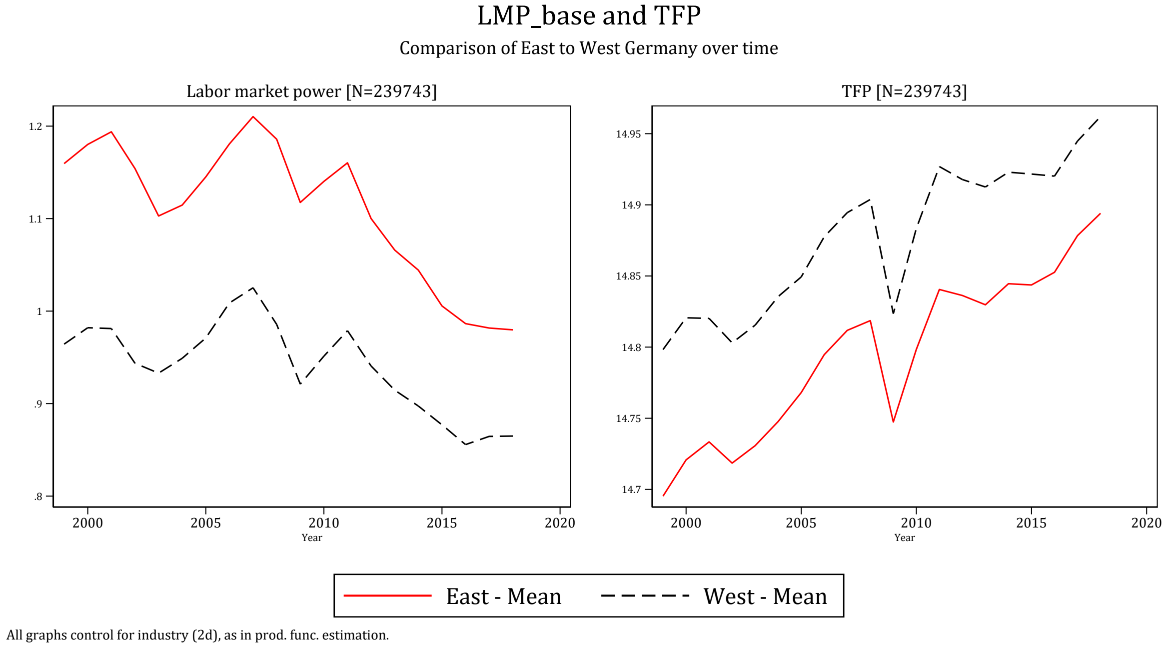


Figure 2: Labor market power, productivity and R&D across regions in 19 European countries

Figure 3: 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

stronger when including additional controls for firms' employment and capital stock levels to account for firm size.

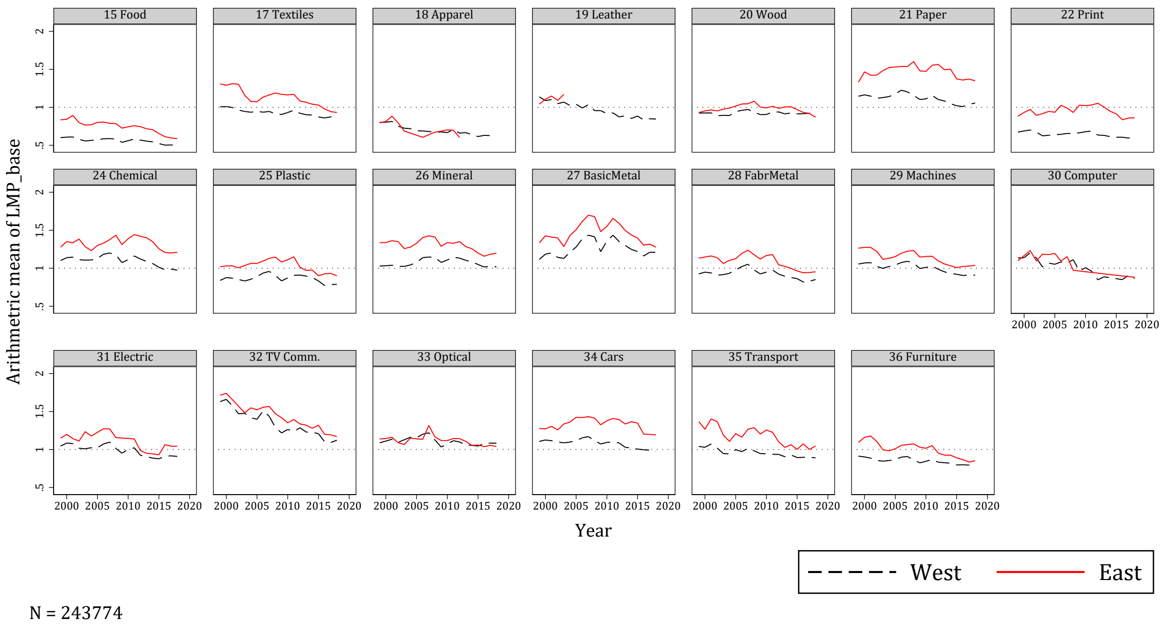
Fact 2: LMP is higher for East German firms across most industries and size classes. Figure 4 shows that higher East German wage markdowns, our measure of LMP, are a common feature across almost all two-digit industries in our data. In the only few exceptions, LMP is on a similar level in both regions, e.g. in the *apparel* industry or the *computer* industry. Similarly, Figure 5, 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 3 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 6 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.

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

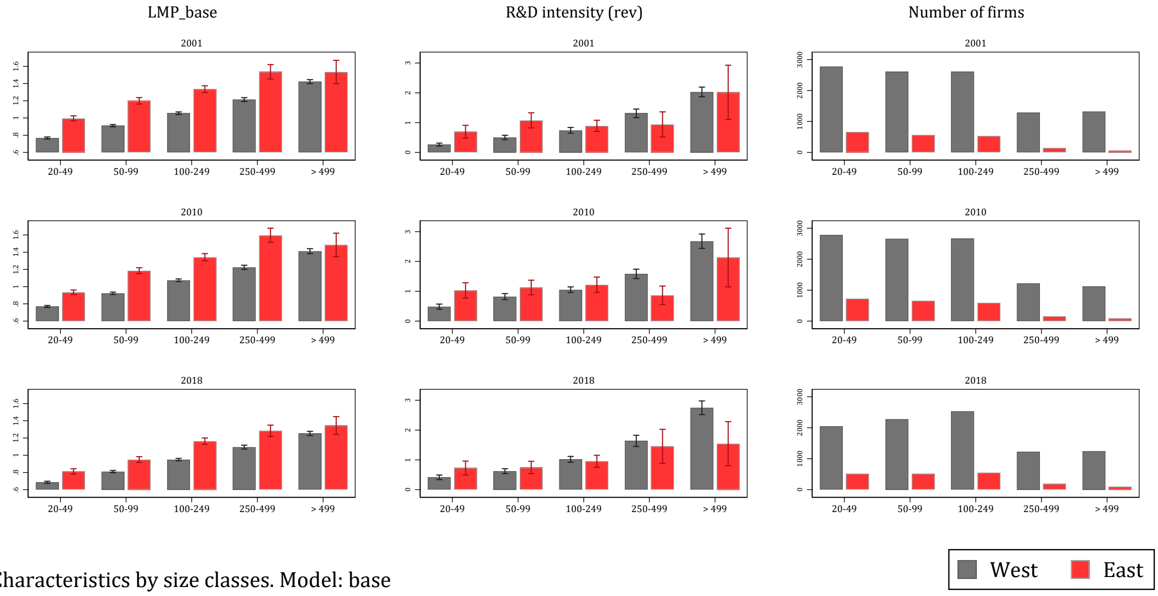
	Dependent variable:	
	Firm labor market power	
	(1)	(2)
East = 1	0.177***	0.214***
	(0.00588)	(0.00485)
Log labor		-0.000786
		(0.00301)
Log capital		0.154***
		(0.00199)
Observations	266,713	266,713
R-squared	0.241	0.495
Industry4d FE	Yes	Yes
Year FE	Yes	Yes
Firms	47394	47394

Figure 4: 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

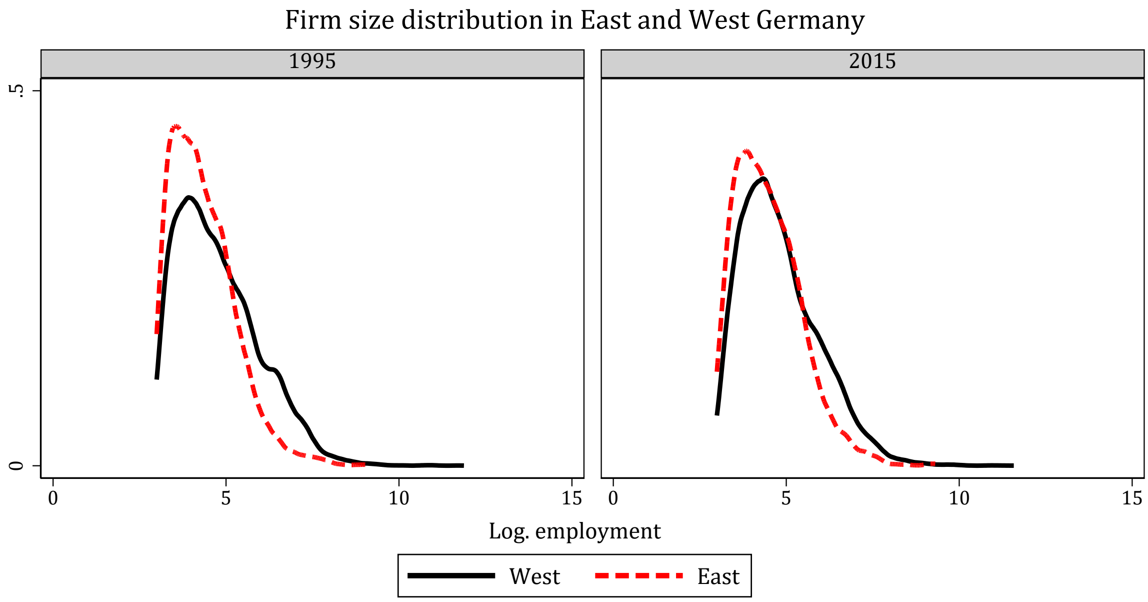
Figure 5: LMP and R&D intensity, by size class



Characteristics by size classes. Model: base

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

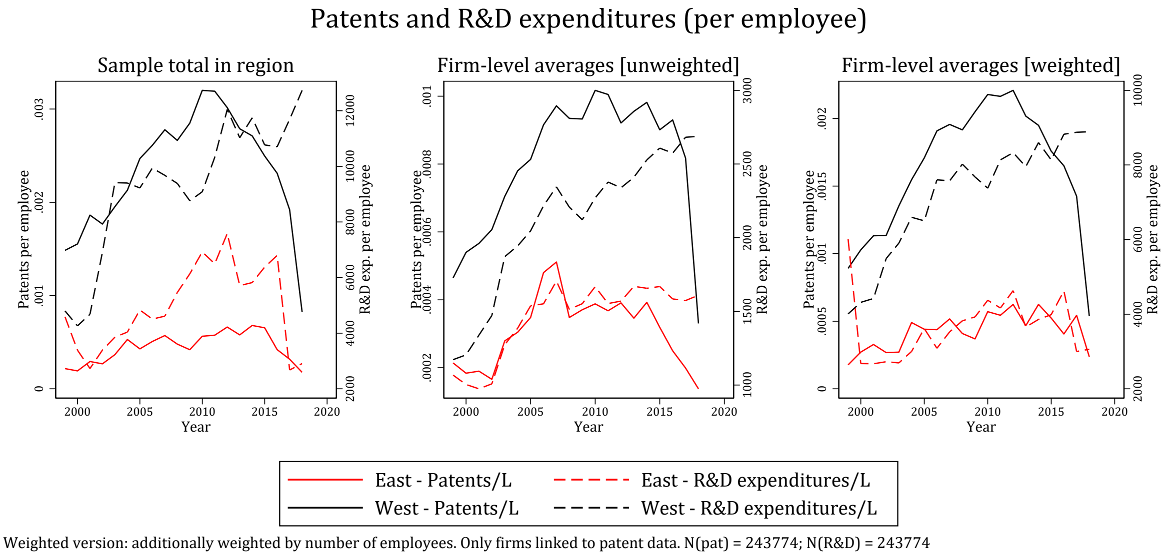
Figure 6: Firm size distribution, 1995 - 2015



N(1995) = 12356; N(2015) = 11592

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 7: 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

Fact 4: East German firms are less innovative. Figure 7 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 3. 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 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*

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

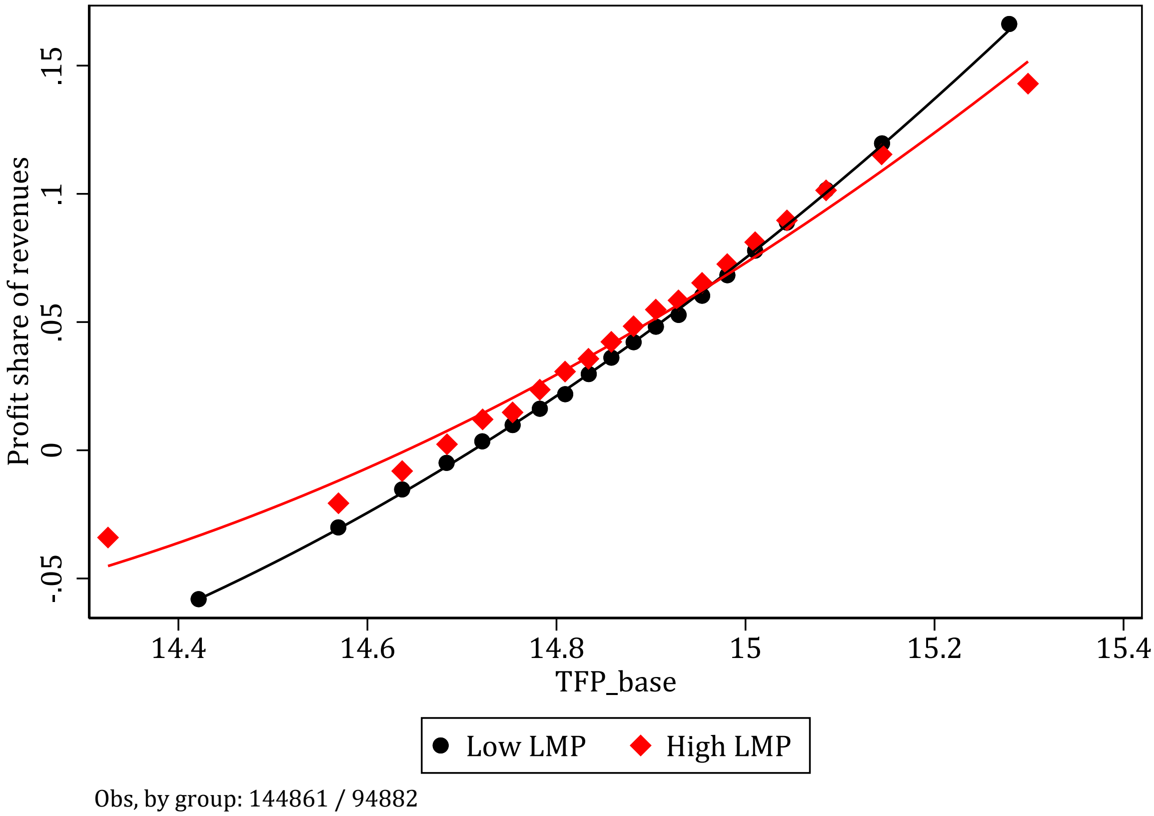
VARIABLES	(1) R&D/sales	(2) R&D/sales	(3) R&D/sales	(4) R&D/sales	(5) R&D/sales
Labor market power		-0.00783***	-0.00655***	-0.00887***	-0.00830***
		(0.000478)	(0.000447)	(0.000507)	(0.000531)
East = 1				0.00411***	0.00438***
				(0.000433)	(0.000453)
East = 1 # LMP_base					-0.00240***
					(0.000786)
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.

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 5, Column 2 reveals interesting heterogeneities with respect to R&D investment across firm sizes. This part of the figure reports average R&D intensities by size class. While Eastern firms, on average, invest less in R&D, small East German firms actually exhibit higher R&D intensities compared to their Western counterparts. Only when considering firms with more than 250 employees, we find that West German firms are more R&D intensive. Since larger firms typically exhibit higher R&D intensity in general and contribute the majority of overall R&D spending, the relatively small R&D activity in large firms and the general scarcity of large firms are key reasons why East Germany is lagging behind in innovation. In combination with Fact 5 (the negative correlation of R&D with LMP), this finding is particularly interesting, and might indicate that small firms have higher returns from investing in R&D in the East in a high labor market power environment, while the opposite seems true for larger firms.

Figure 8: 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

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 8 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.

6 Theoretical model

In this section, we develop an endogenous growth model that captures the mechanism through which LMP lowers the incentives to innovate and allows us to quantify the size of the effect. We rely on XXXX main building blocks: First, imperfect competition on product markets ensures that firms with different productivity can exist in the market. Second, these firms face different labor supply curves, i.e. they have labor market power. Third, these firms invest in increasing their productivity, which also drives aggregate productivity.

While this model adheres to the spirit of our empirical exercises, we make some simplifications for tractability reasons: First, we drop intermediate and capital inputs and focus on labor l as the only production input.

XXXXXXXXXXFor now, our 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).

6.1 Demand

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

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

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

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

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

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

Thus, the price the final goods sector is willing to pay for variety j rises with its quality and falls with its quantity. The producer of variety j is a monopolist for that specific variety, but faces the indirect competition of the other producers. The monopolist produces with $z_j = \bar{A} * l_j$, i.e. the higher the average quality in the economy, the higher is the actual production, which keeps the economy on a balanced growth path. Eq. 7 yields firms' profits as

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

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

6.2 Production and labor markets

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

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

The labor market power situation of each firm is characterized by the size of its pool of attached workers S^l_f and the elasticity of worker preferences ε. Both Maassen et al. (2024) and Bachmann et al. (2022) use these types of preferences. We do not commit to a particular formulation, since it is not necessary to explain aggregate productivity differences, which is our aim. However, this precludes us from making welfare statements.

6.3 Static profit maximization

To maximize their static profits, firms have to choose the optimal labor l_j. Insert equation 9 into 8 and optimize w.r.t labor l_j to arrive at optimal labor $l^*_j = [\frac{(1-\beta)*K_1*A^{\beta}_j*(S^l_f)^{\varepsilon}}{(1+\varepsilon)}]^{\frac{1}{\varepsilon+\beta}}$. That is, equilibrium labor is increasing in productivity and the size of the firm's worker pool and declining in product substitutability. The wage elasticity ε has an ambiguous effect on firm size: If productivity is very low, the firm might actually increase production above what it would do in a competitive equilibrium to maximize the gains from its labor market power.

To understand the relationship between our model and the empirical exercise in section 4, we can use this optimization result: our measure of labor market power γ is defined as the ratio between the marginal revenue productivity of labor and the wage, which is

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

i.e. our empirical measure γ exactly recovers the labor supply elasticity ε. This highlights that equation 9 implies a constant labor supply elasticity faced by the firm, an assumption backed into our entire strand of literature.

The equilibrium employment l^*_j also implies equilibrium profits as

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

Where π^* is a complicated constant function of the model parameters. This result is analogous to the original Akcigit and Kerr (2018), where profit was linear in productivity. Note that in the special case of $\varepsilon = 0$, profit is linear in A_j and the model collapses to its predecessor. The additional curvature in profits is introduced by the labor market, where unproductive firms can reap additional profits by wage markdowns. The most unproductive firms gain the most in percentages, but a larger size is necessary to gain in absolute terms, so that 'not to unproductive' firms gain the most. Panels 1 and 2 of Figure **??** report firm revenue and profits as a function of productivity A_j.

6.4 Technology and R&D Decision

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

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

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

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

6.5 Dynamic Optimization

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

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

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

$A_j) - V(A_j)]$. Because of the non-linearity of profits, it is not enough to assume the economy is in steady state ($\dot{V}(A_j) = 0$) to solve the problem analytically.

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

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

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

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

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

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

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

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

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

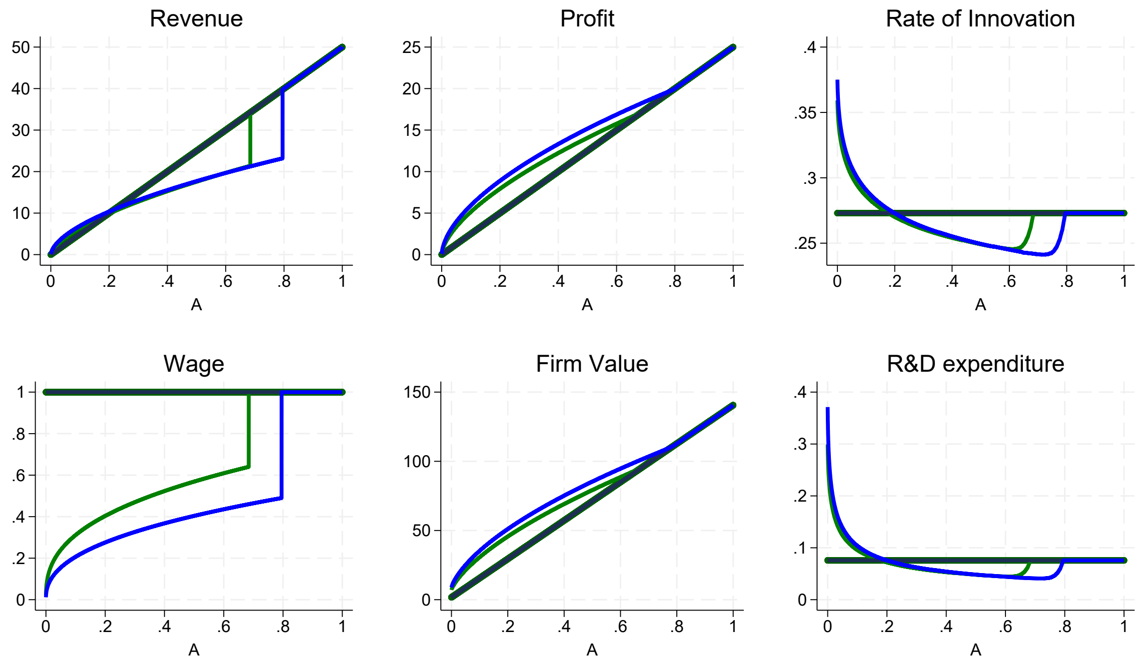
$$r * V(A_j, \varepsilon, \bar{A}) - \dot{V}(A_j, \varepsilon, \bar{A}) =$$

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

Since the value of a firm in a competitive market $\kappa(A_j + \lambda\bar{A}) + \Xi\bar{A}$ is known, the equation has two unknowns (optimal z_j and the firm's value. The first derivative w.r.t. z_j yields the second equation that allows for an analytical solution to this problem. However, while the solution is analytical, it is still iterative in the sense that it goes backward innovation by innovation. Figure 9 reports firms' strategies and evaluation for different levels of ε.

Reviewing firms' strategies, high labor market power firms mostly are smaller, less innovative

Figure 9: Firms' optimal strategies and value functions



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

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

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

The main novelty of our analysis shows how LMP disincentivizes innovative activity. This reflects our empirical fact 6, showing a strong negative correlation between LMP and R&D intensity. It should be noted that R&D is only one option how firms can improve their Hicks-neutral productivity. Especially small firms might instead favor different productivity enhancement methods, such as adopting technology or learning best practices. Therefore, one could even view our negative correlation between R&D and labor market power as a lower bound. Our model also shows that this effect is expected to be different across firm sizes. As we document in Fact 5, small firms in East Germany actually invest more into R&D than their Western counterparts. Since firms' labor market power leads to short-run higher profits, in particular at low levels of size (or productivity), initially productivity improvements are especially lucrative for firms with high labor market power (empirical fact 6). However, these relatively higher profit gains quickly diminish, as seen in Figure 9. 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.

7 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.

7.1 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.

8 Conclusion

Labor market power is an important and persisting friction, especially in structurally weak regions in advanced economies. Beyond its well-documented negative effect on wages and overall production output, we develop a framework in which labor market power can dynamically influence firms' decisions to conduct R&D and to innovate. We propose that this has an adverse effect on aggregate productivity growth and could cause development disparities, such as those seen between East and West Germany, in terms of productivity, wages and GDP.

To study the relationship between labor market power and productivity-enhancing R&D investments of firms, we use rich German manufacturing-sector firm-level panel data that allows us measure firms' R&D activity and to estimate state-of-the-art measures of firm-specific labor market power and total factor productivity. Using this data, we establish several novel facts on firms' labor market power. Most notably, we show that small low-productivity firms have higher R&D investment rates if they have high labor market power, while, oppositely, large high-productivity firms have lower R&D investment rates if they possess high labor market power.

We rationalize this key fact as well as several other empirical findings using a simple model in which firms' incentives to invest into R&D are shaped by their labor market power. The model can replicate the above observations as well as many other empirical regularities regarding firms' labor market power in Germany.

While we focus on the German case, additional European evidence from the CompNet dataset shows that labor market power is negatively associated with R&D activity and labor productivity also in other regions in Europe, which suggests that our findings are potentially relevant for many other countries.

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

Innovation activity plays a critical role in determining the long-term growth of productivity and the economy in general. Our finding that labor market power is associated with lower innovation activity highlights an important new dimension through which labor market frictions can lead to aggregate welfare losses. Not only statically, but dynamically and persistently.

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Appendix

A Data

A.1 Overview on variables and summary statistics

Table A1: Variable definition in the German microdata.

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

Table A2: 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.[9] 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.[10]

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

[10] Mertens (2021) 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.[11] The output elasticity of labor (and analogously for any other input) is:

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

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

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

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

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

Solving (1) by deriving a firm-specific output price index. As aggregating output quantities (measured in different units) across a firm's product portfolio is not meaningful, we follow Eslava et al. (2004) and construct a firm-specific price index from observed output prices. We use this price index to deflate observed firm revenue.[12] We construct firm-specific

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

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

Törnqvist price indices for each firms composite revenue from its various products in the following way:

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

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

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

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

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

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

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

cal and four-digit industry-specific input prices. Conditional on elements in $B(.)$, we assume that there are no remaining input price differences across firms. Although restrictive, this assumption is more general than the ones employed in most other studies, which implicitly assume that firms face identical input and output prices within industries.

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

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

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

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

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

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

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

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

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

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

where for convenience, we defined:

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

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

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

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

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

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

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

D Robustness checks

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

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

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

Table 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.