Labor market power and innovation
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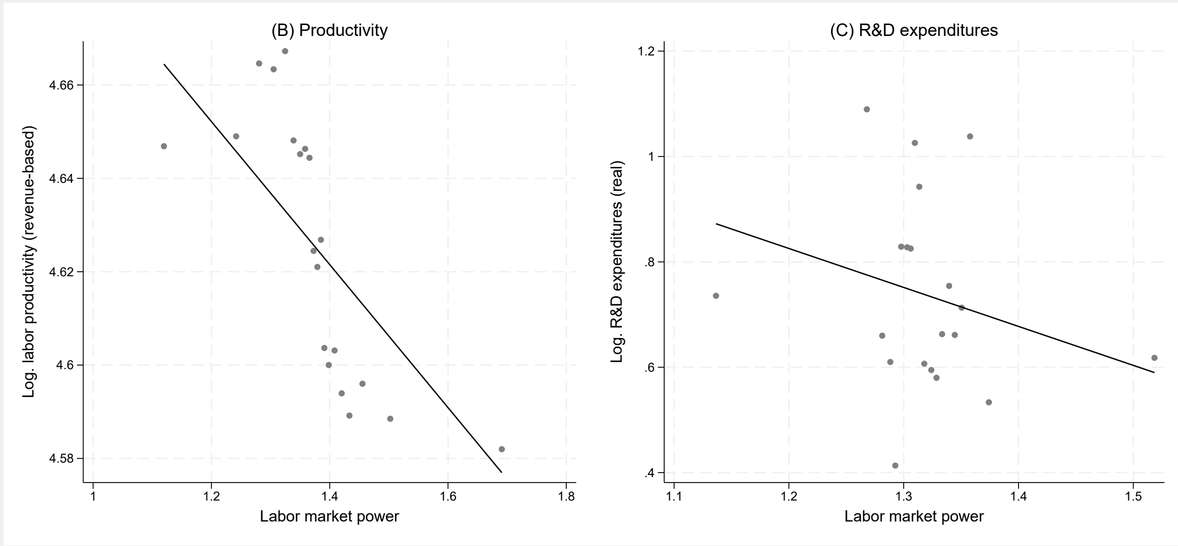
Abstract: This paper studies the effect of labor market power (LMP) on firms' innovation decisions and consequently its effect on aggregate growth. We find that LMP is particularly prevalent in structurally weak regions across Europe and is negatively correlated to aggregate productivity and innovation activity. We study the effect of LMP with a firm level data set on the German manufacturing sector 1999-2016. We estimate firms' labor market power, the effect on innovation on productivity & profits and estimate the value of additional innovation for firms in the poorer, high labor market East German states and in West Germany. The average firm in the East German states gains between 0.3 and 0.7 Million €more from innovation than its equivalent in West Germany. This relationship is reversed for low productivity firms: Low productivity East German firms gain about 1.5 Million €more, since innovation allows them to grow to a moderate size and profit from the high labor market power environment. A one standard deviation change in LMP explains a differential of 10% of firm-level R&D spending. As a result, Eastern firms are less productive, smaller, but not necessarily less profitable. Our theoretical framework provides an explanation for these patterns: Firms with high labor market power have less incentives to innovate as their profit function depends to a relatively lesser extent on total factor productivity (TFP). With this new channel and its implication on firm dynamics we provide a new explanation for the persistence of low productivity in structurally weak regions and in particular for the persistence of the productivity gap within Germany.

1 Introduction

This paper studies the effect of labor market power (LMP) on firms' innovation decisions and consequently its effect on aggregate growth. While innovation is the main driver of growth in the economy, it requires firms to engage in costly R&D. They only undertake it if additional profits earned through the improved technology justify it. We estimate that labor market power has a substantial dampening effect on innovation in the German manufacturing sector, especially in the poorer East German states.

To arrive at this conclusion, we use state of the art estimators for productivity and labor market power in a comprehensive data set of firms from the German manufacturing sector between 1995 and 2016, following Mertens (2022). We then recover the relationship between profits and productivity for different segments of firms, to show that firms with high labor market power have higher profits, but that their profits rise slower with higher productivity. We estimate firms' value functions with and without innovation from these findings, following Peters et al. (2017). The average firm in the East German states (with high labor market power) gains between 0.3 and 0.7 Million €more from innovation than its equivalent in West Germany. This relationship is reversed for low productivity firms: Low productivity East German firms gain about 1.5 Million €more, since innovation allows them to grow to a moderate size and profit from the high labor market power environment. This mirrors firms' actual behavior: The least productive and smalles East German firms innovate more than their West German counterparts, but medium and large East German firms innovate substantially less than their counterparts in the West. This result is the main contribution of our paper.

The setting of Germany is particularly fruitful to study these effects because the former German separation resulted in an economic division that can still be seen for productivity and wages 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. But our results are not only relevant for the German context. The regional economic disparity in Germany is not a unique case. Instead, within many European countries, regions exhibit vast differences in productivity, wages and, in line with our proposition, labor market power. This suggests that the mechanism we are studying in detail for Germany, also holds for other countries. Figure 1 shows a regression using micro-aggregated data at the NUTS2 regional level from the 9th vintage of the CompNet dataset for 19 European countries (excluding Germany). Here, average firm labor productivity in panel (A) measured as log. value-added per worker and R&D expenditures in panel (B), are regressed on a measure of labor market power. The utilized CompNet LMP measure is based on Dobbelaere and Mairesse (2013) and similar to the one we are estimating in this paper and describing in Chapter 3.2. The clear and significant negative correlation between LMP and productivity or R&D suggests that labor market power is a likely culprit in hampering innovation, productivity and ultimately GDP per capita across Europe. Even more clearly Figure 2 shows for three illustrative large European countries that the LMP is an important predictor of productivity differences, particularly within country. Value-added per worker and LMP are shown here for three within-country bins. There is a clear negative



Source: CompNet 9th vintage, unconditional NUTS2 dataset. x-axis: CE58_markdown_l_5_mn; y-axis = (A) PV02_lnlprod_rev_mn, (C) log(FV30_rrd_mn). Controlling time, country and NUTS2 FE.

Figure 1: Labor market power, productivity and R&D across regions in 19 European countries

correlation between the two variables which can be seen in the graph because the regional colors tend to be either starkly blue or starkly red, but rarely the combination of both. This shows that high labor market power is particularly prevalent in structurally weaker regions. Motivated by this clear relationship on the European level, we therefore propose that labor market power has a detrimental effect on long-term development by disincentivizing firms from engaging in innovation.

Our result adds to the literature on non-convergence between countries, but is even 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. Our paper departs from their approach by actually estimating labor market power and its effect on innovation in a microeconometric setting before using it for modelling. We also provide evidence that the dampening effect of labor market power on innovation is not an exclusively East German phenomenon and make no assumptions about the cause of said labor market power in poor regions. 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 TFP convergence in Germany.

We follow the literature on production function and markup estimation building on De Loecker et al. (2016), following Mertens (2022) closely. However, we are the first to use these estimation techniques to explore the relationship between labor market power and innovation.

We also make use of the literature on estimating the effect of innovation on the firm level, going back to Griliches (1979). We follow Peters et al. (2017); Aw et al. (2011); Doraszelski and Jaumandreu (2013) in joining production function estimation with an intertemporal value

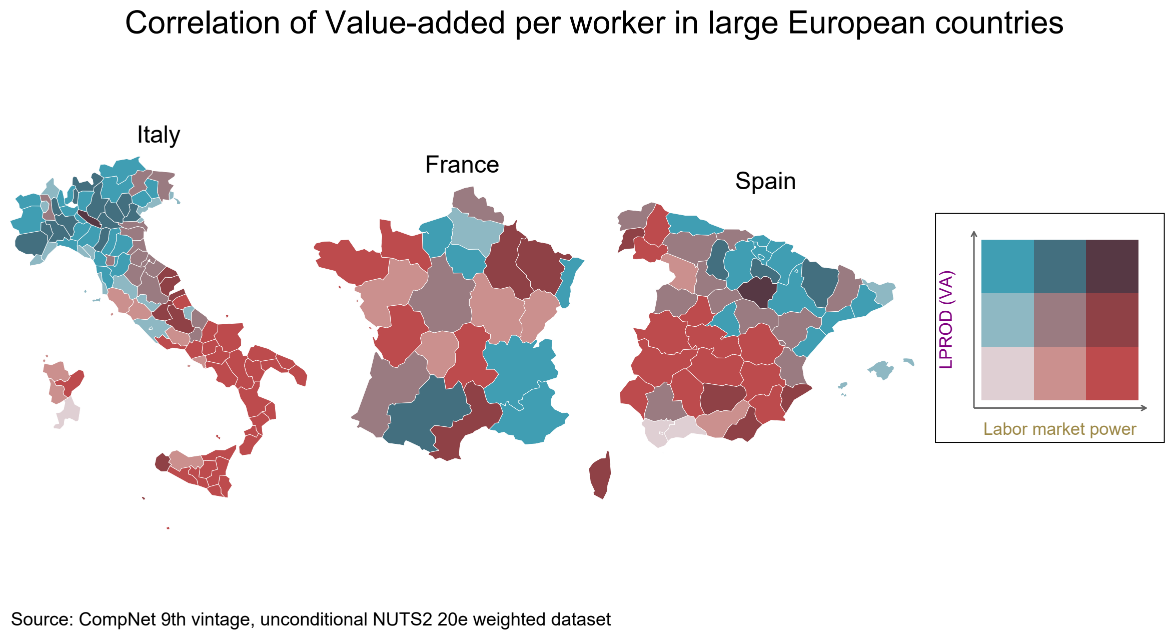


Figure 2: Labor market power and labor productivity in large European countries

function optimization to understand both the effects of and the firms' motivation for innovation. We are the first to use these techniques to study the effect of market power on firms' innovation decision.

In estimating the detrimental effects of firms' market power, we connect to a large literature documenting and discussing the increase in firms' market power using production function estimation techniques (Barkai, 2017; De Loecker and Warzynski, 2012). However, this literature focuses on product market power, while we study the effects of rising labor market power as depicted in Mertens (2022). The effect of product market power on innovation is ambiguous because some product market power is necessary to incentivize firms to innovate (Aghion et al., 2005, 2006). At the same time, incumbents who already enjoy high markups due to past innovation generally have a lower incentive for innovation (cf. Akcigit and Kerr (2018)). But to our knowledge, ours is the first paper analysing the dynamic incentives of firms with labor market power to undertake innovation. 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. Here, we look into 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).

The remainder of the paper is organized as follows: Section 2 describes the data sources we use for the estimation. Section 3 lays out our theoretical framework and the estimation techniques we use to recover productivity and labor market power. This section also discusses the results from this estimation. Section 4 uses the results from the previous section to estimate the value function of both high and low labor market power firms, taking into account the possibility of future type switches and the effect of current and future innovation. Section 5 concludes.

2 Data

Our empirical analysis is based on the AFiD data, a representative panel of the German manufacturing firms. The data comprises all manufacturing firms with at least 20 employees, but the full set of variables is only available for a roughly 40% representative stratified sample, drawn roughly every 4 years. We use this subset for our analysis because it is exceptionally rich in terms of variables. Due to only firms with more than 20 employees being obligated to answer the survey, we cannot study entry and exit dynamics. But in Germany, large manufacturing firms perform the bulk of R&D and are thus of most interest to us. In addition to the standard variables needed for production function estimation, the information on R&D expenditures and wages, which we proxy by firm-level labor costs per employee, is especially pertinent. Capital stocks have to be imputed using the perpetual inventory method, but investments and depreciations are available for several different categories of capital goods to allow for precise imputation. Furthermore, we use the available information on revenues per product to construct firm-specific price indices and deal with output and input price bias when estimating production functions (Mertens, 2022).

Table 1 shows some basic descriptive statistics in our main dataset, separately for firms in East and West Germany which make up 16% and 84% of the sample, respectively. Since we have panel data for 17 years, the number of observations shows the total number of firm-year observations in our sample from 1999 - 2016. The unique number of firms covered is 38878, of which we observe 9000-12000 per year. Since R&D expenditures are included in the AFiD data only from 1999 onwards, this is where our main sample starts, but in some of the figures and

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

Table 1: Main sample: Descriptives for East and West Germany, 1999-2016, source: AFiD

tables, where R&D expenditures are not shown, results are shown also for earlier years until 1995.

For a set of firm-level characteristics, Figure 3 shows the evolution of averages and medians across East and West over time. The Western level for each of these moments is normalized to one and the Eastern level can be seen in relation to that. Starting at the top left and going horizontally through the plots, the first one shows that the capital-labor ratio is very high in the East. This is likely a result of hefty investment subsidization, especially in the 1990s for the East. But a high capital endowment also makes workers generally more productive in a standard production setting, as we develop in section 3.1. However, at the same time we see the reverse for material inputs in the next panel. Here Western firms seem to endow workers with significantly more or higher-quality materials than the East. The third panel in the top row shows the Eastern labor share. Here it is noteworthy that it is not significantly different from the West, but it is generally smaller. Higher capital endowments and lower material inputs cancel each other out. But strikingly wages (measured as average labor costs per employee) are significantly and persistently lower in Eastern Germany. Together with the result for the labor share this points at a sizeable gap between Eastern workers' contribution to production and their compensation. Panel 5 shows labor market power directly. The measurement is explained in detail in the following chapters, but the graph clearly shows that firms have consistently higher LMP in the East. We will explore this pattern in detail in Chapter 3. The role of product market power is not first-order concern of our study, but as Mertens and Mueller (2022) we can see that it is higher in the West. Since in our context firms maximize their profits through revenue-productivity growth, we factor in this lower level of markups in the East. R&D intensity is here shown as an average across all firms, regardless of size and without other controls. The fact that it is not lower than the West's during most of the sample period shows an important heterogeneity, in particular across firm sizes as we will show in Chapter 3.3. As we will discuss in detail, smaller Eastern firms are actually not lagging behind in innovation, but larger firms, who are the main driver of innovative activity, do lag behind. We will propose LMP as an important mechanism driving this.

Lastly, profits as a share of revenues are converging to Western levels very strongly. Note that this convergence keeps up until 2010, whereas the convergence in TFP, as documented in the literature and shown in Figure 4 in Chapter 3.3 has stopped since the year 2000. Together with the lower wage levels, this provides additional indirect evidence on the role of LMP: Eastern firms make profit not through TFP growth, but through cost-saving on the labor market. While

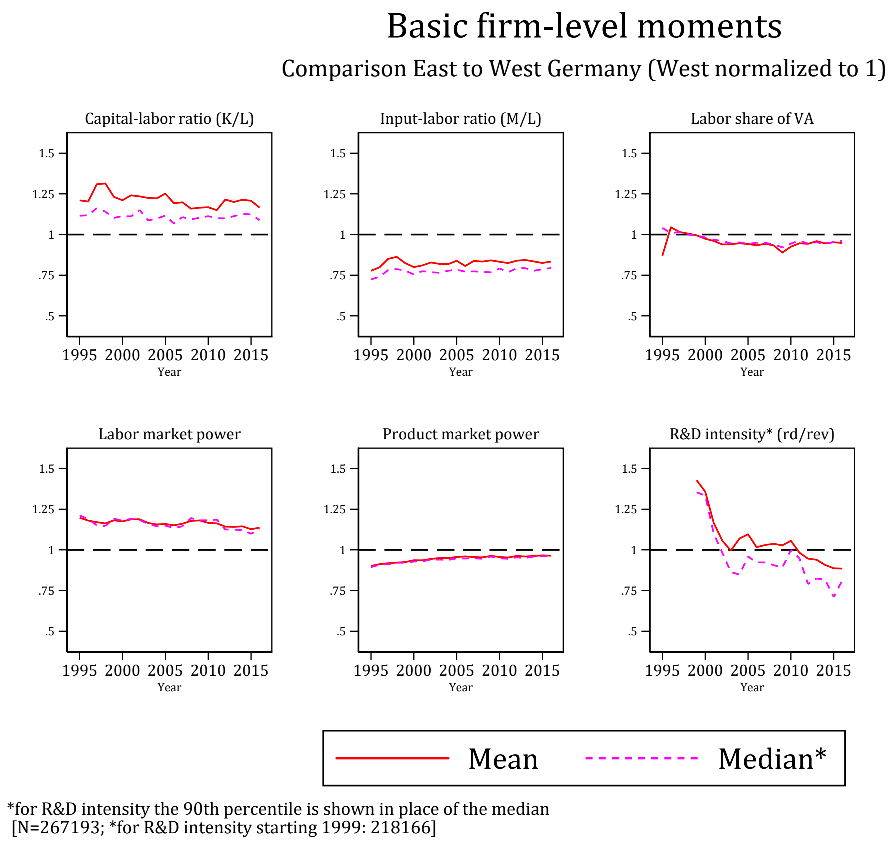


Figure 3: Basic firm-level moments, normalized to West-German level; source: AFiD, own calculations

profits remain lower in the East, the faster convergence for profits highlights the importance of our mechanism. Profit dynamics will be discussed in Chapters 3.3 and 4.

With the facts from Figure 3 as motivation to analyze these East-West differences further, our theoretical and empirical framework of labor market power and its impact on productivity and innovation is laid out in the following chapter.

To augment this data further, we merge patent applications on the firm level: We take patent applications from all major patenting authorities collected by the European Patent Office (PATSTAT 2016b) between 1995 and 2014 and extract the strings describing the patent applicant. We then use a string matching algorithm to match these strings to AMADEUS, a large and (for identifiers) comprehensive database of European firms, to retrieve a business registry number for patent applicants. Lastly, we use this number to match patent applications 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. Consequently we set the number of patents to 0 for firms where we do not observe patents for a given year.

3 Labor Market Power in Germany and Its Effects

3.1 Theoretical Framework

This section studies firms' decision making in a static world, following Mertens (2022), which again is building on Dobbelaere and Mairesse (2013). We develop the estimators we use to gauge the productivity and labor market power of firms and discuss the effect of both variables on innovation incentives.

A firm i produces physical output in period t and sells it to maximize

$$\pi_{i;t} = P_{i;t}(Q_{i;t}) * Q_{i;t}(L_{i;t}, K_{i;t}, M_{i;t}) * A_{i;t} - w(L_{i;t}) * L_{i;t} - r_t * K_{i;t} - z_t * M_{i;t} \tag{1}$$

$Q_{i;t}$ represents total physical output and $L_{i;t}$, $K_{i;t}$, and $M_{i;t}$ denote labor, capital, and intermediate inputs used in the production of $Q_{i;t}$. Firm-specific total factor productivity is denoted by $A_{i;t}$. Productivity is assumed to be multiplicative, i.e. Hicks-neutral. Firms set wages to demand labor on imperfectly competitive labor markets characterized by an upward sloping function $w(L_{i;t})$, but intermediate input markets are flexible and intermediate input prices z_t are exogenous to firms. For the remainder of the discussion, we also abstract from potential capital market imperfections, which are not in the focus of our analysis. Note that both the output price and the wage potentially depend on firms' decisions. The only restriction on the functional form of eq. (1) is that it is twice differentiable.

Regardless of both the demand specification and the labor supply curve the firm is facing, we can use the FOCs with regard to labor and intermediate inputs (i.e. the firm's cost minimization problem) and rearrange to arrive at a measure of the labor market power of the firm $\gamma_{i;t}$:

$$\gamma_{i;t} = \frac{\frac{\partial R_{i;t}}{\partial L_{i;t}}}{w(L_{i;t})} = \frac{\theta^L_{s;t}}{\theta^M_{s;t}} \frac{z_t * M_{i;t}}{w(L_{i;t}) * L_{i;t}} \tag{2}$$

where $w(L_{i;t})$ denotes the wage the firm is paying and $R_{i;t} = P_{i;t}Q_{i;t}$ denotes its revenue. In a competitive setting, the wage would equal the marginal revenue product of labor $\frac{\partial R_{i;t}}{\partial L_{i;t}}$. If the firm has labor market power, it pays wages that are lower than $\frac{\partial R_{i;t}}{\partial L_{i;t}}$. Likewise, if the workers have labor market power, firms might be forced to pay more. Alternatively, one can express labor market power as the ratio of output elasticities for labor $\theta^L_{s;t}$ and for intermediate outputs $\theta^M_{s;t}$ times the ratio of the expenditures for these inputs. This works because intermediate inputs are sourced on a competitive market by assumption and thus give a 'clean' comparison (De Loecker and Warzynski, 2012). So, γ_{it} in eq. (2) defines our direct measure of labor market power as used in the empirical section as well.

For the empirical part of our paper, we remain agnostic about how labor market power comes about. The empirical evidence points towards multiple explanations: Firms in concentrated labor markets, large firms and capital intensive firms all ceteris paribus have higher labor market power. Moreover, firms located in regions characterized by a lower union density and a lower rate of collective wage agreements (such as East Germany) possess higher labor market power conditional on several controls (Mertens, 2022). Another explanation, explored by Bachmann et al. (2022), names monopsony power in East Germany as the culprit. While our empirical results confirm this, our framework and mechanism allows for different sources of LMP as well.

Labor market power defined this way is closely related to adjustment costs for labor. Without adjustment costs of some kind, firms would also never be willing to pay more for a worker than his marginal revenue productivity, so the measure would have to be above 1. This is the case for the vast majority of firms in our sample. However, the literature on labor relations has suggested multiple microfoundations of market power for workers with adjustment costs, e.g. McDonald and Solow (1981) show that labor unions can both create the firing frictions and then bargain for higher wages, Kline et al. (2019) shows that firms might pay above MRPL if workers need firm specific human capital (and are thus not easily replaced) and a whole literature details the interdependency between search and matching labor markets and the resulting Nash bargaining. Garin and Silverio (2023) collect several such arguments in a general framework. The conceptual intertwinedess of adjustment costs and market power makes it hard to differentiate between the two, but following the arguments in (Mertens, 2022) and given the fact that we observe mostly firm labor market power, we abstain from adjustment costs in our framework.

Another key determinant of firm behaviour is a firm's productivity, $a_{i;t}$. The firms incentive to innovate depends on $a_{i;t}$, since all inputs $(L^*_{i;t}, K^*_{i;t}, M^*_{i;t})$ are increasing in $a_{i;t}$. To understand the incentive the firm has for innovating, i.e. increasing its productivity, we differentiate (1) with respect to $a_{i;t}$ and differentiate the result again with respect to labor market power. Because firm productivity is multiplicative, the Envelope Theorem yields the following expression in terms of optimal revenue size $P_{i;t}(Q^*_{i;t}) * Q^*$:

$$\frac{\partial \frac{\partial V_{i;t}}{\partial a_{i;t}}}{\partial \gamma} = \frac{\partial \frac{\partial \pi_{i;t}}{\partial a_{i;t}}}{\partial \gamma} = \frac{\partial P_{i;t}(Q^*_{i;t}) * Q^*_{i;t}(L^*_{i;t}, K^*_{i;t}, M^*_{i;t})}{\partial \gamma} \tag{3}$$

In all classes of models usually considered, where returns to a single factor of production (here labor) are positive, but decreasing, the following holds: The firm capitalizes on labor market power by producing less then in a competitive labor market, thus decreasing its labor demand, because otherwise it would eventually equate its MRPL with the wage, given that w(L) is an increasing function. Keeping production, i.e. utilized labor, at a lower level allows it to depress wages and earn rents. As a result, the quantity produced and, consequently, revenues will also decline. Firms with labor market power are therefore on average smaller than similar firms without LMP. Since the expression in eq. (3) serves as an index of firms' size, $P_{i;t}(Q^*_{i;t}) * Q^*_{i;t}(L^*_{i;t}, K^*_{i;t}, M^*_{i;t})$, the returns to innovation are lower for firms with labor markt power than for those without, if all other parameters were the same. Note that output market power could potentially exacerbate this effect if firms also optimize for lower output quantities due to monopoly power on output markets.

Given our result that LMP reduces incentives in any case, it is important to note that labor market power itself could be a function of size. This would be the case particularly in the case of monopsony as proposed by Bachmann et al. (2022) because a firm needs to have a critical size to exert monopsony power in the first place. Our framework encapsulates this special case, but it would make γ additionally a function of size. This would counteract the aforementioned disincentive to grow up to a size threshold beyond which our mechanism would work in an unrestricted way. Therefore, as in the model by Bachmann et al. (2022) there would be an optimal firm size.

After showing how LMP affects innovation decisions in an adverse way, we need to measure LMP and a, i.e. TFP. The next section discusses how to estimate these objects in our framework.

3.2 Identification

Measuring labor market power according to equation (2) requires an estimate of the output elasticities of the production function. We estimate these elasticities using the standard control function approach with price data, based on De Loecker et al. (2016). Intuitively, the control function aims to solve the endogeneity problem when estimating production as a function of inputs that arises because firms that receive a positive productivity shock also increase (some of) their inputs to capitalize on the positive shock. Timing assumptions about which inputs can be be changed at what point allow one to recover both the production function parameters and firms' productivity. We estimate the log physical production function implied in equation (1) using the approach of Mertens (2022).

Thus, we aim to estimate

$$q_{i;t} = \sum_{n=0}^{n=2}\sum_{o=0}^{o=2}\sum_{q=0}^{q=2} \beta_{n,o,q} l_{i;t}^{q} * m_{i;t}^{n} * k_{i;t}^{o} + B(.) + g(.) + \zeta_{i;t} + \epsilon_{i;t} \tag{4}$$

where the production function is specified as a flexible second order polynomial of the log input factors ($l_{i;t}$,$m_{i;t}$,$k_{i;t}$). Note that the classical Cobb Douglas production function is a special case of this so called "translog" production function. However, with a Cobb Douglas production function, firms' output elasticities are identical for all firms by assumption, which we are not willing to assume for our application, since in that case all differences between the expenditure shares for input goods would have to be attributed to input market power (eq. 2).

Note that the left hand side variable is not revenue, but physical quantity $q_{i;t}$. In order to build a quasi quantity for firms with more than one product, we follow Eslava et al. (2004) and deflate revenue with a firms specific price index to purge any price effects.

$B(.)$ is the price control function, which De Loecker et al. (2016) introduced into the literature. It controls for unobserved variation in input good prices and consists of a second order polynomial of the firms specific price index, a weighted average of a firm's market shares in its various product markets, the federal state of the firm's headquarter and an industry dummy as well as the log. input terms ($l_{i;t}$,$m_{i;t}$,$k_{i;t}$). The intuition for this specification is that output prices and input expenditures are shown to proxy for unobserved input price changes.

In a similar vein, $g(.)$ describes a productivity control function following Olley and Pakes (1996) and Levinsohn and Petrin (2003) that tackles the endogeneity problem inherent to Eq. 4: Firms react to increases in productivity by adjusting their inputs. This decision is explicitly estimated in the control function, i.e. the level of current productivity is estimated as a second order polynomial of past state variables (export status, the number of products a firm produces, its average wage, employment) and of the most flexible inputs (materials): Since the material input decision of the firm depends on observed productivity and state variables, this functions captures the part of productivity the firm could observe when making its decisions, while it is unobserved by the researcher.

Lastly, $\zeta_{i;t}$ describes the productivity innovation, i.e. unexpected, lasting change in firm productivity e.g. due to a successful innovation. $\epsilon_{i;t}$ is an i.i.d. productivity shock or (depending on interpretation), measurement error in the dependent variable.

Once the estimation is concluded, we obtain the production function, from which we back out productivity for every firm and compute the output elasticities of said firms at their current point on the production function. We can also obtain labor market power, since we now have estimates for all its constituent terms in eq. 2.

3.3 Results - Labor Market Power in Germany

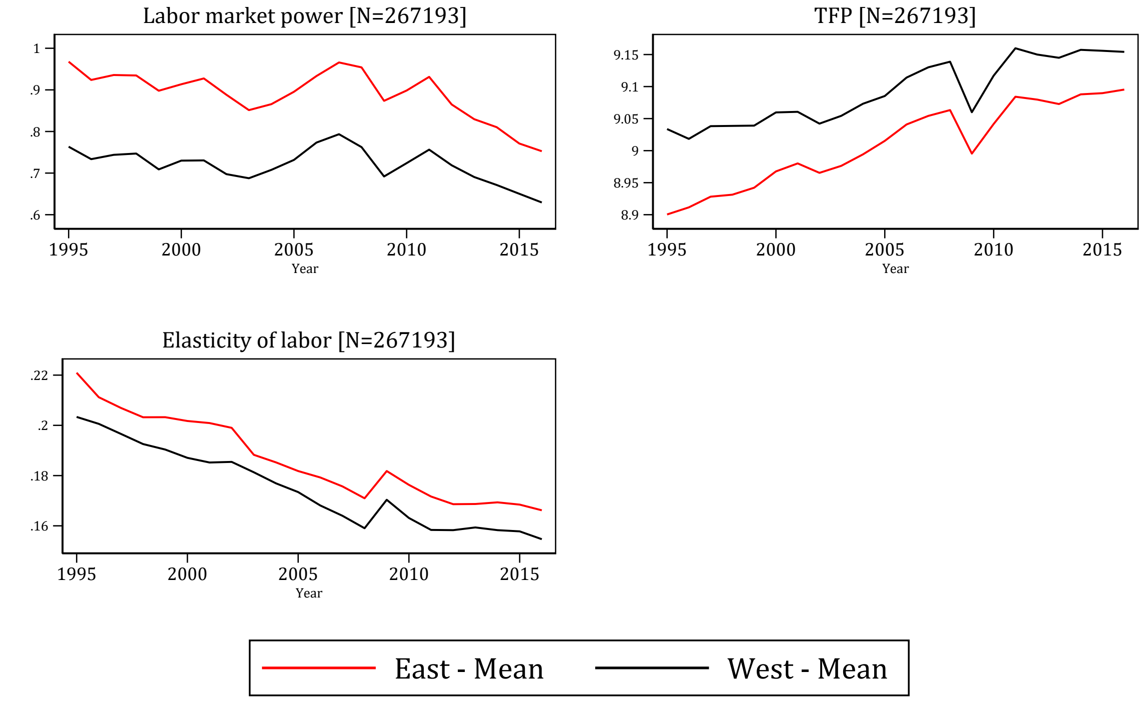
In this chapter we show the results for the relationship between labor market power and innovation employing the production function estimation tools and leveraging our rich dataset of German manufacturing firms. We document features of the data our model of the effect of labor market power has to replicate.

3.3.1 East German firms have higher labor market power, lower TFP and produce with more labor

As a starting point, Figure 4 describes the differences between East and West Germany in our firm level variables of interest over time. We can confirm the literature (cf. Mertens and Mueller (2022)) in documenting the persistent TFP gap between East and West Germany at the firm-level in our data as well. As shown in Figure 4 at the top right, Eastern firms have a consistently lower TFP than their Western counterparts within the same industry. Initial TFP convergence until the year 2000 has stopped since. The third panel in Figure 4 shows the average firm-level labor elasticity that we estimated in the process to back out TFP and LMP. It is consistently higher for Eastern firms highlighting the importance of labor in their production function. This indicates that Eastern firms utilize the fact that labor is relatively cheaper for them, as shown next.

Table 2 shows that this result also holds when including more granular firm-level controls in a pooled OLS regression with our unbalanced firm panel from 1999 - 2016: Labor market power is consistently higher in East Germany in column (2). The estimated coefficient means that Eastern firms have a roughly 0.177 higher labor market power, i.e. the percentage differential between the marginal revenue productivity of labor and the wages paid is 17.7pp larger compared to Western firms and in total almost 22.7% larger compared to the competitive equilibrium case, where LMP would be equal to 1. The constant in column (2) can be interpreted as the Western level. Column (3) shows that this East differential in LMP even increases when controlling the firm-size structure by including log. labor (l) and log. capital (k) into the regression. This is not surprising since small firms, of which there are more in East Germany, have less LMP in general. Also, note that the employment size coefficient turns insignificant when East is included compared to the baseline in column (1). This is another indication that

Figure 4: LMP and TFP gap



All graphs control for industry (2d), as in prod. func. estimation.

Notes: Evolution of labor market power, TFP and output elasticity of labor 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

	(1)	(2)	(3)
VARIABLES	LMP_base	LMP_base	LMP_base
l	-0.0210***		-0.000786
	(0.00306)		(0.00301)
k	0.163***		0.154***
	(0.00206)		(0.00199)
East = 1		0.177***	0.214***
		(0.00588)	(0.00485)
Constant	-1.390***	1.050***	-1.381***
	(0.0232)	(0.00363)	(0.0225)
Observations	266,713	266,713	266,713
R-squared	0.465	0.241	0.495
Industry4d FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firms	47394	47394	47394

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

Table 2: LMP differences in Germany, Source: AFiD, own calculations

the size distribution in Eastern Germany is highly endogenous when considering labor market power: The result that LMP is higher in the East is evidently not driven by few large Eastern firms, but instead by the entire distribution. These results give us confidence that the LMP in the East is ubiquitously higher than in the West. This holds for different size classes as well (cf. Figure 6, left column). This main finding is in line with Bachmann et al. (2022) whose analysis implicitly attributes lower size classes and wages in the East to labor market power. With our direct measure derived from the estimated production function we can confirm their findings and complement their analysis. Additionally, we can give an alternative explanation to their finding that firms are smaller in the East, through the channel of innovation.

3.3.2 Firms in East Germany innovate less

As discussed in section 3.1, a firm with higher labor market power at the margin will have less incentive to innovate: It produces less units of its good and this will save less from higher productivity. Thus, R&D expenditures should be lower in the East and likewise for patenting. This goes against classical convergence theory, which would predict firms in the East to engage more in growth, i.e. innovation through the lens of our model. This is not what we find in reality: In Figure 5 we plot both R&D expenditures divided by the number of employees, i.e. innovation input intensity, and patenting per employee, i.e. innovation intensity measured from successful innovation. To also cover the extensive margin of innovation, the graph considers firms that are matched to the patent data as described in Chapter 2 and firms without a match, whose patents are assumed to be 0. Hence, this figure shows both the extensive and intensive margin of innovation activity. We can see that sample totals (left), unweighted averages (middle) and sales-weighted averages (right) all confirm the same picture: The East is lagging behind

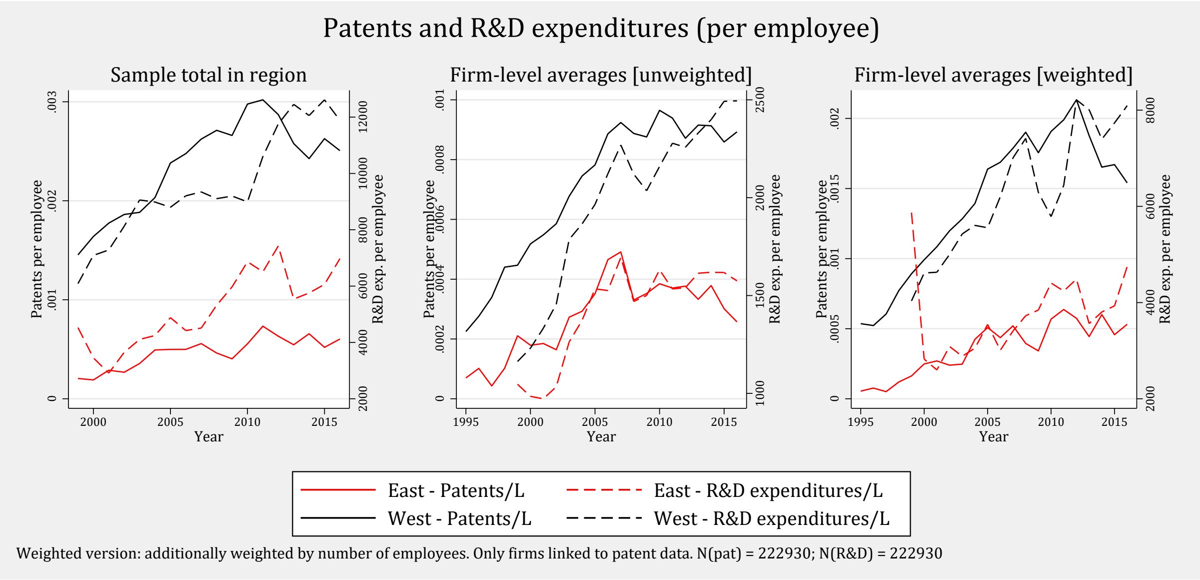


Figure 5: Patenting and R&D expenditures, across East-West-Germany; source: AFiD and PATSTAT, own calculations

in innovation by a significant margin. In the following we will relate this gap in innovativeness directly to LMP.

3.3.3 Firms with high labor market power innovate less

Table 3 shows our core result in a pooled OLS regression. Column (1) has a baseline where R&D intensity measured as R&D over sales is regressed on log. employment size and log. capital as well as a set of 4-digit industry and year fixed-effects. It shows that larger firms on average have higher R&D expenditures 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. Introducing LMP in column (2) shows that there is a strong negative correlation between LMP and R&D intensity. Given a standard deviation of LMP of 0.45 in the sample, this point estimate in terms of a standard deviation increase in LMP 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 R&D intensity is between 1 and 3% for firms in the sample (with few exceptions). In column (3) we show that this result holds virtually unchanged also when controlling firm fixed-effects in the panel regression. Column (4) introduces an East dummy. Interestingly, the East coefficient is strongly positive, after controlling for LMP here, which suggests what we know: LMP is higher in the East, but apart from that East is actually positively correlated with R&D intensity. Catch-up growth potential does seem to play a role here, but we can uncover it only after taking out the variation of LMP. More intriguing for the East-West-context even, introducing an interaction in column (5) is even more illuminating: LMP has an even higher adverse correlation with R&D intensity in the East compared to the West. A potential explanation for this would be that LMP is more systematic and more predictable in East Germany, exacerbating the innovation-dampening effect in our model. The result in columns (4) and (5) also highlights once again

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.

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

that we need to be mindful of the firm composition in the East.

Table 4 repeats the analysis of Table 3, column (5), but adding patents to the picture. In column (1) the specification is repeated and shows the results for the sample with patents as in Table 3. Column (2) reinforces this for annual patents, with one exception: The negative coefficient of LMP by itself is halfed in size and not significant anymore. This could be due to patents being a more noisy measure than R&D expenditures in a given year. But the effect of East and the interaction between LMP and East are very strong here too. In fact, now the interaction effect clearly supersedes all other estimated coefficients. This again shows the LMP is likely more restrictive in the relatively poorer East. This is in line with our theoretical model which predicts that firms with LMP grow only up to a certain threshold after which growth is disincentivized. It is also possible that the nature of LMP is fundamentally different in the West and thus having less bite on the accumulation of patents in the West.

3.3.4 There are fewer large firms in East Germany

Our model predicts fewer large firms in East Germany, very much in line with the finding by Bachmann et al. (2022) that firms in the East are generally smaller due to their labor market power. The reasoning is similar to that by Bachmann et al. (2022): Firms choose an optimal size based on their LMP which is determined by the labor supply's wage elasticity. Figure 6

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 4: Different measures of R&D intensity; source: AFiD and PATSTAT, own calculations

shows these differences in the size distributions across East and West Germany for three different years (rows of plots, 1999, 2007 and 2016). The last column shows the firm size distribution by size-classes. Note that the Eastern bars for the number of firms generally decline much more rapidly than for the West as going up in the size-class from left to right. In particular, the largest firms, with at least 500 employees, constitute a miniscule part of the Eastern firm distribution, whereas they make up almost an eighth of the Western firm size distribution in our sample.

Figure 6 also confirms our main mechanism. First of all, LMP is considerable higher in the East (first column) across all size-classes and time periods. But for the largest firms the difference to the West is lower, which speaks particularly to monopsony power playing a role in the East. Furthermore R&D intensity in the second column is not generally lower for the East. Indeed, it seems to be higher for some of the smaller size-classes across all years. But with the exception of the outlier-prone year 1999,[1] the larger size-classes lag behind their Western counterparts in R&D spending as a share of revenues. The graph suggests our mechanism by itself: Firms do engage in R&D in the East, but only up to a certain size, after which they stop growing. The next column shows labor elasticity which tends to be higher in the East

[1] 1999 is the first year with R&D expenditures in our data and during this time R&D spending was still heavily subsidized in the East. We therefore interpret the value for the small sample of large firms to be driven by outliers, here. At the expense of such noise, we however do not clean outliers for R&D spending, because we believe that the tails of the distribution contain particularly important information for R&D activity.

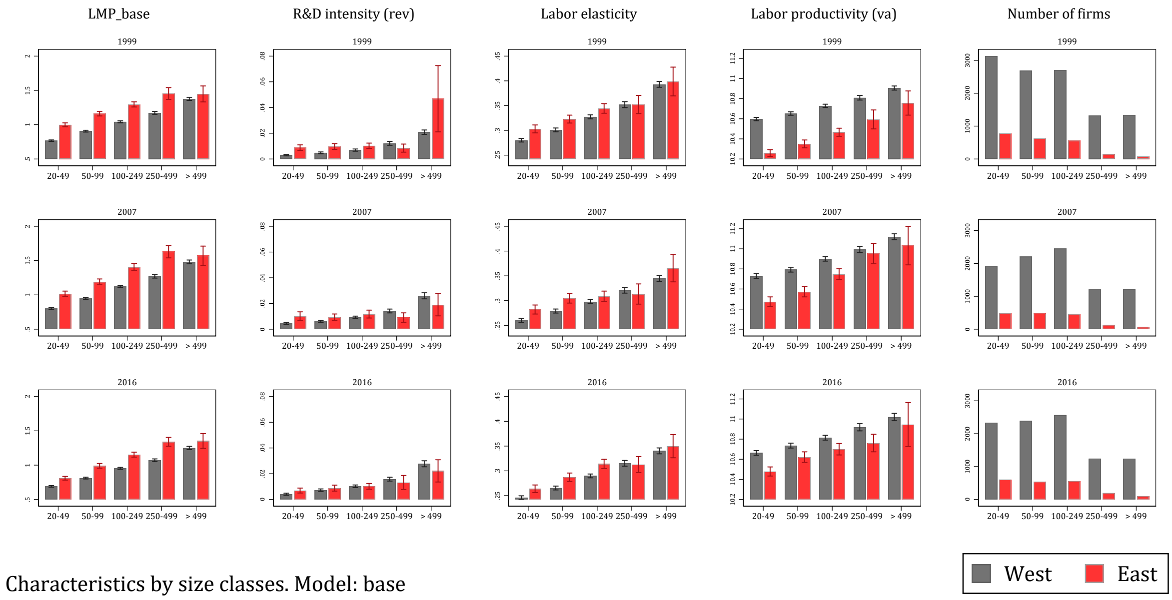


Figure 6: Firm size distribution across East and West, with key characteristics, source: AFiD, own calculations

showing more importance of the input labor in production. Lastly in column four, the labor productivity, i.e. value-added per employee, is generally lower at all size classes in the East, but more so for the smaller firms. This shows to us that the productivity gap is driven in large part by the mid-sized firms that are constrained according to our LMP mechanism.

3.3.5 Firms with higher labor market power have higher profits, but gain less from TFP increases

Through the lens of our model with profit-maximizing firms, profits are the best predictor for firm behaviour. Figure 7 shows the main relationship we investigate here. In it we control for

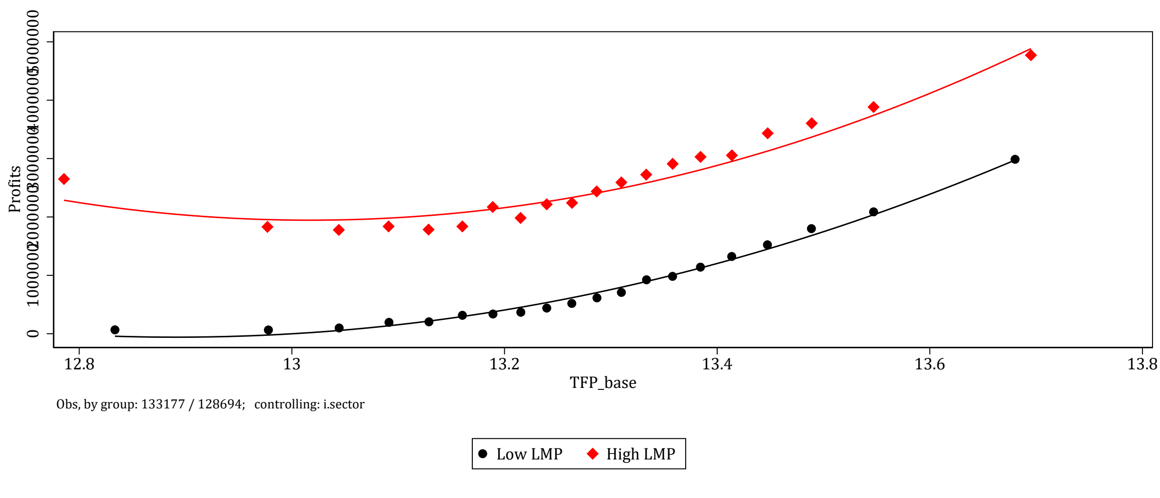


Figure 7: Productivity and profits under different LMP regimes, source: AFiD, own calculations

2-digit industry fixed-effects. Firm profits on the y-axis are generally increasing in productivity (TFP_base). However, the plot shows the relationship for two regimes of labor market power: high LMP firms above the median in the firm distribution (across East and West), and low LMP firms which are below. For a given level of productivity, high LMP generally yields higher profits. But there is an important distinction in the two lines: Their slope is different. While high LMP firms have larger profits, the relationship is flatter than for the low LMP firms. In contrast, firms with low LMP have a steeper profit increase upon increasing TFP incrementally. This means, in line with our model, they have a greater incentive to innovate than firms with higher LMP.

4 Incentives to innovate

We have documented persistent differences in the innovation intensity and outcomes and firm profits between firms with and without labor market power. In this section, we will take this approach to the data and estimate the parameters of Eastern and Western firms' intertemporal optimization and the resulting value functions.

To keep the problem computationally tractable in the actual estimation, we bin all x variables (productivity, labor market power, labor share, research intensity) and define a type θ as a combination of these characteristics. Then, in discrete time, a firm's value is

$$V^f(\theta_t) = \pi(\theta_t) + \beta \sum_{x=1}^{X} p(\theta_{t+1} = x|\theta_t) * [V^f(\theta_{t+1}) - V^f(\theta_t)] \tag{5}$$

Where $\pi(\theta_t)$ is current profits net of research costs, β is the discounting factor and θ_{t+1} indexes the possible types next period: $p(\theta_{t+1}|\theta) * [V_t^f(\theta_{t+1}) - V_t^f(\theta)]$ denotes the value gain for the firm if its type next period were θ_{t+1}, multiplied with the probability of this actually occurring.

The firm's only decision in this notation is to pick its current type ty. While the firm cannot affect productivity, labor market power or its labor production function coefficient and so cannot choose among all types, it can choose its R&D. The optimal type to pick will depend on the change in $p(n|\theta)$ for any level of R&D spending - and the transition probabilities from that future type. Using this notation of the problem, we remain agnostic about the reasons for labor market power or the functional forms of any of the relevant variables. However, assumptions about these objects are not necessary to solve the problem numerically.

In the empirical exercise, we define 36 types as the intersections of 3 TFP levels (firms with less than 90% of sector level TFP, firms with more than 110% and those in the middle), 3 levels for the output elasticity of labor α (firms with less than 90% of sector level α, firms with more than 110% and those in the middle), 2 R&D levels (firms with and without R&D expenditures) and firms in East and West Germany (and thus with high and low labor market power). The resulting 36 types are all filled with between 439 and 2614 firm observations, which allows us to see the characteristics of firms in the groups with reasonable accuracy. This is especially pertinent for the Transition matrix between the types $p(\theta_{t+1} = x|\theta_t)$. Thus, $\pi(ty)$ and $p(n|ty)$ can be estimated by their sample analogues.

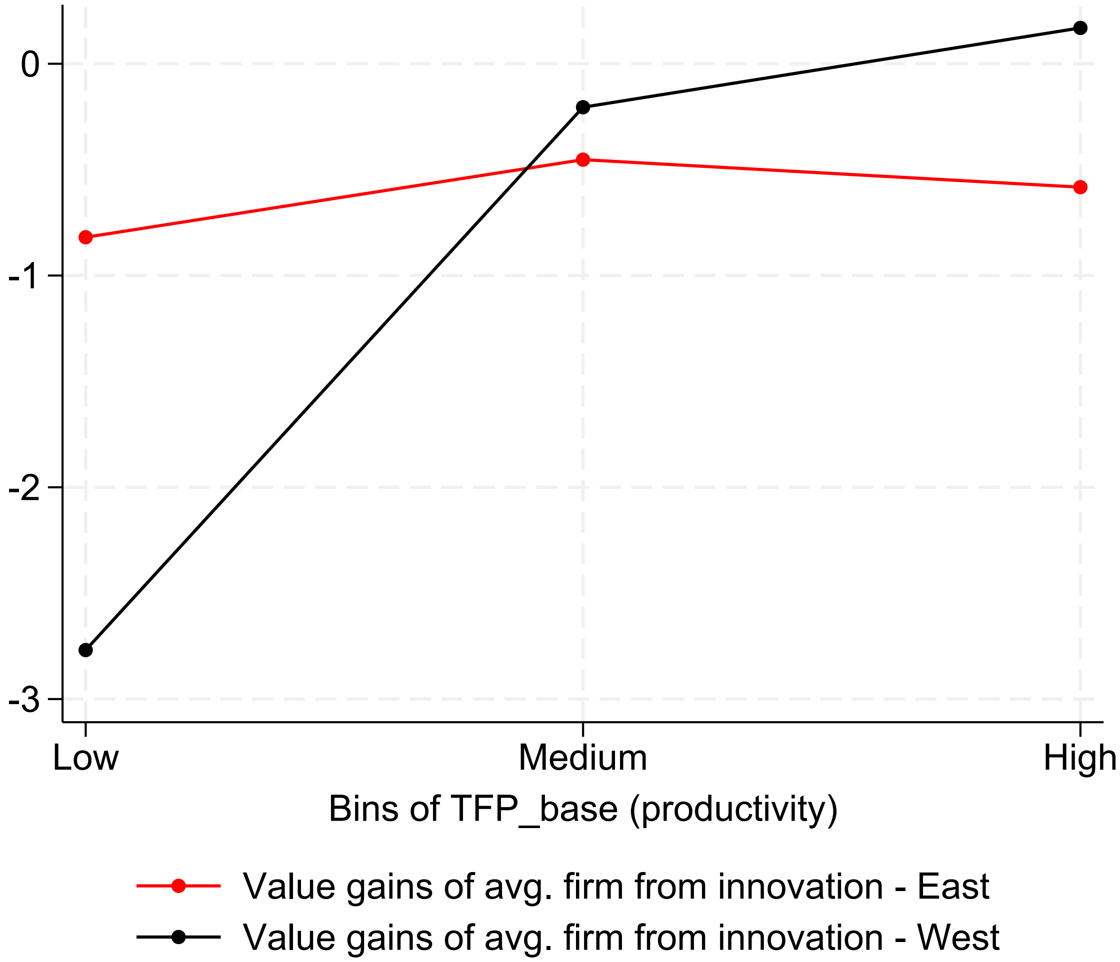
The transition matrix between the different bins has a high degree of stability, as is in line with the literature (Peters et al., 2017), which diagnoses low and declining business dynamism across all dimensions for Germany (Mertens, 2022): R&D performing firms have a higher than 90% chance to continue with R&D, while non-R&D firms have a less than 10% chance to start. Likewise, firms have a 85% chance to stay in their labor elasticity bin and a 75% chance to stay in their productivity bin. R&D mainly increases the chance to exit the lowest productivity bin, while the effects for higher productivity firms are much less clear and depend on type. The effects of R&D on the labor elasticity are even smaller and have less clear directions.

Estimating firm value instead of static profits from eq. 5 requires contraction mapping following Peters et al. (2017). This numerical technique solves the simultaneous equation problem in equation 5 accounting for the fact that the firm value given any type θ contains itself and all other types. Figure 8 depicts the value of starting R&D for the average firm for high and low labor market power firms across the TFP distribution. This not only includes the direct profit increase, but also the additional value gains from improving the position of the firm for future R&D or increasing the chance to gain a different production function in the future. Note that the returns to innovation are lower in East Germany, except for low productivity firms. This is in line with a model where some firms size is necessary to exploit the higher labor market power in East Germany, i.e. a monopsony model as described before. But the flatter relationship between profits and productivity dis-incentivizes further R&D. It is also in line with the firms' observed behavior, as discussed in section 3.3: Small East German firms are actually more likely to do R&D than their West German counterparts, while the relationship reverses for large firms, which results in overall less R&D in East Germany.

5 Conclusion

Labor market power is an important and persisting friction, especially in structurally weak regions in advanced economies. Beyond its static effect of lowering wages and decreasing overall production output, we develop a framework in which labor market power dynamically influences firm decisions to innovate. We propose that this has an adverse effect on aggregate growth and could cause development disparities, such as those seen between East and West Germany, in terms of productivity, wages and GDP. To show this we develop a general framework in which innovation incentives are negatively related to firms' labor market power and test our predictions using a rich dataset of German manufacturing firms across both regions. Our estimation not only confirms the literature regarding the lower TFP and smaller firm sizes in Eastern Germany, but also shows that labor market power is higher for all firms in Eastern Germany. We then show that this can explain the observed lower R&D activity in the East. In particular we estimate that value gains from innovation are lower especially for larger firms in Eastern Germany, which is in line with labor market power in the form of monopsony as documented in the literature. We propose that Eastern firms, instead of competing with new innovations, retain profits by maintaining labor market power and, thus saving labor costs. Additional evidence from the CompNet dataset shows that labor market power is negatively associated to R&D activity and labor productivity also in other regions in Europe, which is particularly pertinent for low-income

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



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

regions.

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

Additionally we aim to estimate the effect of labor market power on innovation in a causal setting by leveraging the introduction of minimum wages in Germany. Effective minimum wages can diminish labor market power by forcing firms to increase their wages, which in our framework can incentivize firms to grow. This could serve as an identification scheme to disentangle potential confounders from the effect we are studying, which we have abstained from so far. But we can also analyze the effect that the minimum wage introduction had on labor markets and in particular on the mechanism proposed in this paper.

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

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