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Matthias Mertens

Author

Matthias Mertens
Halle Institute for Economic Research (IWH) – Member of the Leibniz Association, Department of Structural Change and Productivity, and The Competitiveness Research Network (CompNet)
E-mail: matthias.mertens@iwh-halle.de
Tel +49 345 7753 707

Editor

Halle Institute for Economic Research (IWH) – Member of the Leibniz Association

Address: Kleine Maerkerstrasse 8
D-06108 Halle (Saale), Germany
Postal Address: P.O. Box 11 03 61
D-06017 Halle (Saale), Germany

Tel +49 345 7753 60
Fax +49 345 7753 820

www.iwh-halle.de

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Abstract

I study how labour market power affects firm wage differences using German manufacturing sector firm-level data (1995-2016). In past decades, labour market power increasingly moderated rising between-firm wage inequality. This is because high-paying firms possess high and increasing labour market power and pay wages below competitive levels, whereas low-wage firms pay competitive wages. Over time, large, high-wage, high-productivity firms generate increasingly large labour market rents while selling on competitive product markets. This provides novel insights on why such "superstar firms" are profitable and successful. Using micro-aggregated data covering most economic sectors, I validate my results for ten other European countries.

Keywords: inequality, labour market power, monopsony, rent-sharing, superstar firms

JEL classification: J31, J42, L10

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The data used in this article can be obtained from the statistical offices of Germany and from the website of the Competitiveness Research Network. Details on data access are provided in the online Appendix A.

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1 Introduction

The past 40 years witnessed a fundamental transformation of labor markets, reflected in globally declining labor shares, falling between-firm worker dynamism, and rising wage and income inequality. Technological change and globalization are often seen as main contributors to these trends. Yet, recent research started a new debate on the role of monopsonistic corporate market power in explaining this labor market transformation and in affecting economic welfare (e.g. Naidu et al. (2018); Berger et al. (2019); Mertens (2020a); Azar & Vives (2019, 2020); Stansbury & Summers (2020); Manning (2021)).[1] This work spurred discussions on benefits of intensifying the regulation of firms' labor market power, which in the enforcement of most antitrust regulations plays only a tangential role, at least when it comes to the success of actual litigations (Naidu et al. (2018); Marinescu & Hovenkamp (2019)). Yet, to assess the desirability of such policies, we need to understand the causes and consequences of labor market power and how labor market power is distributed across firms and employees – a topic to which this article contributes.

Monopsonistic labor market power reflects in wages being below the marginal revenue product of labor (MRPL) and much of the recent industrial organization and economic law literature focuses on this firm-side labor market power while ignoring cases where employees use their labor market power to drive wages above firms' MRPL. Yet, accounting for both, employer- and employee-side labor market power, is crucial for understanding how labor market power affects labor markets because wages also depend on rent-sharing processes between workers and firms.

[1] See also the ongoing debate on the role of declining employee bargaining power for stagnating wage levels and rising inequality (e.g. Card (2001); Dustmann et al. (2009); Antonczyk et al. (2010); Bell et al. (2019)).

Against this backdrop, I first derive an efficient bargaining framework allowing for arbitrary *firm- and employee-side* labor market power.[2] I introduce firm-side labor market power into this setting by assuming that only a part of the workforce bargains with firms over rents. Wages of the remaining workforce are determined in a monopsonistic labor market. Combining different first order conditions then recovers a measurable expression for firm- and even firm-worker-group-specific labor market power (the wedge between firms' wages and MRPL). Due to duality of firms' cost minimization and profit maximization, my approach also delivers product markup expressions identical to the framework of De Loecker & Warzynski (2012) and thus conceptually extends their work to include firm- and worker-side labor market power.

Although the literature applies similar approaches, existing research either i) invokes a polar labor market structure sorting firms into monopsonistic and efficient bargaining regimes (e.g. Dobbelaere & Mairesse (2013); Dobbelaere et al. (2020)) or ii) completely abstracts from either rent-sharing or monopsonistic wage setting power (e.g. Card et al. (2018); Morlacco (2019); Azar et al. (2019)). In contrast, I derive firm- and employee-side labor market power from a single optimization framework that nests existing rent-sharing and monopsonistic labor market models and does not sort firms into specific labor market regimes.

Having derived this framework, I apply it to German manufacturing sector firm-level data from 1995 to 2016, covering a time span of strongly rising wage inequality in Germany (Card et al. (2013)), to study how firm-specific labor market power affects firm wage differences. This dataset is well-suited for my analysis as it contains firm-specific price

[2] Falch & Strøm (2007) also combine bargaining and monopsonistic labor market models, yet without an empirical identification of labor market power. For examples of bargaining models without firm-side labor market power, see McDonald & Solow (1981) and Blanchflower et al. (1996).

information which is key for estimating production functions and labor market power (De Loecker et al. (2016)).[3]

Although there is an important dimension of within-firm-between-worker wage differences for explaining inequality, this article focuses on how firm-specific labor market power relates to *between-firm* wage dispersion, which has been identified as a key factor (if not the most important factor) in contributing to rising wage inequality.[4] As I show, my framework can, however, readily be used to study worker-group-specific labor market power within firms, which I leave for future work. Nevertheless, I prove from these worker-group-specific labor market power expressions that, even without information on firms' workforce compositions, one can calculate unbiased measures of *firm-level* labor market power – the object of interest in this study – from firm-level production and cost data.[5]

Strikingly, I find that a counterfactual elimination of all existing labor market power would *increase* the dispersion of wages between firms. Hence, labor market power contributes to between-firm wage *equality*. This moderating effect of labor market power on firm wage inequality became increasingly stronger in past decades.

The reason for this result is that although large, high-paying, and highly productive firms (recently called "superstar firms") pay above average wages, they enjoy large labor market power and pay wages below their high MRPL.[6] Simultaneously, given market-wide wages,

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[3] This refers to the "price bias" when estimating production functions.

[4] With "between-firm wage differences", I refer to differences in firms' average wages. Several factors contribute to firm wage differences, including labor market power and firm wage premia, worker-firm sorting, and technological differences between firms. I focus on labor market power, but the literature debates the importance of all these factors (e.g. Barth et al. (2016); Lamadon et al. (2019); Bonhomme et al. (2020)).

[5] This is an advantage of my approach compared to the rent-sharing literature, which needs to address changes in firms' workforce composition when identifying rent-sharing parameters/labor market power (Card et al. (2018)).

[6] Several mechanisms can explain this observation. Studying them is beyond the scope of this article. High-paying firms could "hide" behind industry-wide wage standards, allowing them to drive wages below their high marginal products (Mueller & Hirsch (2020)). Or they

smaller and low-paying firms cannot pay wages below their low MRPL. This compresses the firm wage distribution relative to the firm MRPL distribution, causing the firm labor market power distribution to contribute to between-firm wage equality.

Particularly at the upper ends of the wage, size, and MRPL distributions, wage-MRPL gaps are large and increasing. This i) results in wages being below competitive levels in these firms, which strongly contributes to between-firm wage equality (as these firms pay already high wages), and ii) reflects that firm labor market power is increasingly concentrated in large, high-paying, high-MRPL firms. Whereas these firms' labor market power is high and growing, their product market power is low. Hence, these firms generate increasingly high labor market rents while selling on competitive product markets, which offers a novel view on why such "superstar firms" are profitable and successful.

Due to exploiting long and detailed firm-product-level panel data, my analysis is limited to the German manufacturing sector. I address this shortcoming using micro-aggregated data covering most economic sectors for ten other European countries to test the external validity of my results. Most of my findings hold across all countries of my additional analysis, implying that the inequality-moderating effect of labor market power due to "superstar firms" enjoying a huge amount of labor market power is not unique to the German manufacturing sector, but an economic feature of many countries and sectors.

Persistent and rising wage inequality remains to be one of the most intensively debated public policy issues. Recent work increasingly highlights the importance of firm heterogeneity in explaining pay inequality. Song et al. (2019) show that two thirds of the rise in U.S. earnings inequality between 1978 and 2013 are explained by an increase in the

may face an inelastic labor supply at the upper end of the wage distribution due to high-paid workers lacking outside options (e.g. as result of no-pouching agreements as discussed in Gibson (2020)) or preferring non-monetary, firm-specific work amenities over additional money, conditional on receiving high wages (Lamadon et al. (2019)).

dispersion of average wages between firms. Other studies highlighting the importance of between-firm wage dispersion in contributing to wage inequality are Davis & Haltiwanger (1991) for the U.S., Helpman et al. (2017) for Brazil, and Faggio et al. (2010) for the United Kingdom. Similarly, Card et al. (2013) report a substantial contribution of firm wage premia to rising wage inequality in West-Germany between 1985 and 2009.

In addition, several studies highlight a link between increasing firm wage differences and rising firm productivity dispersion (Dunne et al. (2004); Barth et al. (2016); Berlingieri et al. (2017)). Typically, this link is motivated through rent-sharing models where better firm performance results in higher wages (Card et al. (2018) provide a review). In contrast to classical rent-sharing approaches, I derive labor market power from measurable wedges between firms' wages and MRPL. This yields a *firm-specific* measure of monopsonistic and/or worker-side labor market power. Allowing for this type of firm heterogeneity is precisely what uncovers that labor market power counteracts existing firm wage differences. Conceptually, the existing rent-sharing literature cannot provide this insight as it defines rent-sharing elasticities that are *equal across firms*. My findings therefore call for a serious reevaluation of the long-standing view that labor market power causes firm pay differences. If it would, wages should be (unconditionally) higher in firms where workers enjoy higher labor market power. Yet, the opposite is true. In line with Lamadon et al. (2019) and Bonhomme et al. (2020), my study is therefore supportive of alternative factors causing between-firm wage inequality, like (unobserved) worker productivity differentials, differences in firms' production technologies, and worker-firm sorting.[7]

[7] Lamadon et al. (2019) and Bonhomme et al. (2020) find that existing estimates of firm wage premia (firm wage differences after accounting for workforce quality differences and firm-worker sorting) based on the framework of Abowd et al. (1999) are severely upward biased. This implies that firm wage premia, and thus labor market power, are far less important for explaining wage inequality than implied by previous studies.

My study also speaks to the recent literature on rising firm market power and its relation to secular labor market trends (e.g. De Loecker & Eeckhout (2020); De Loecker et al. (2020)). More specifically, I address work focusing on (rising) firm labor market power as explanation for these trends. Much of this young literature concentrates on the importance of (rising) firm labor market power for the fall of labor's share (Mertens (2020a); Gouin-Bonenfant (2020); Brooks et al. (2021)). I instead study the role of firm- *and* worker-side labor market power on the widely documented increase in wage inequality. This also contributes to the general debate on how firm market power shaped the economic environment in past decades.[8]

The remainder proceeds as follows: Section 2 describes the data. Section 3 derives my framework to estimate firms' labor market power and MRPL. Section 4 presents results and studies how labor market power affects between-firm wage inequality. Section 5 discusses robustness tests including a replication of my key results for ten other European countries. Section 6 concludes.

2 Data

2.1 Firm-level data on the German manufacturing sector

My main analysis is based on an administrative firm-level panel dataset for the German manufacturing sector from 1995 to 2016. This dataset is supplied by the statistical offices of Germany and firms are obliged to report. Among others, the data contain information on firms' employment, investment, revenue, and, most importantly, product quantities and

[8] My article also relates to Wong (2020), who studies how firm wage premiums relate to firms' productivity, labor shares, and product and labor market power in France. I focus on how labor market power affects between-firm wage inequality along the firm wage, size, and MRPL distributions and particularly on the time dimension of these relationships, which provides novel insights on mechanisms behind (rising) wage inequality.

prices at a detailed ten-digit product classification (Appendix A.1 provides examples of the product classifications). The information on firm-specific prices and output quantities allows me to estimate a quantity-based production model of firms, which is key in estimating firms' labor market power and MRPL (De Loecker et al. (2016)).

To limit administrative burden, the statistical offices collect this data only for firms with at least 20 employees.[9] Moreover, some variables are only collected for a representative and periodically rotating firm sample, covering 40% of all manufacturing firms with at least 20 employees. The latter includes information on intermediate input expenditures and labor costs by various categories.[10] Online Appendix A.1 details all variable definitions used in this article, explains how to access this data, and provides relevant summary statistics. There, I also discuss how I address changes in sector classifications in my data.

2.2 CompNet data

In section 5, I asses the external validity of my findings using the CompNet data (8th vintage) for ten other European countries. This data contains aggregated firm-level information at the industry (two-digit), sector (one-digit), and country level, including most economic sectors. The data is collected from harmonized data collection protocols that run over administrative firm-level databases of several European national statistical institutes and central banks.

[9] The omission of small firms is unlikely to affect my results as i) my findings are driven by the upper percentiles of the firm wage, size, and MRPL distributions and ii) there is a strong positive relationship between firms' size and wages, labor market power, and MRPL (Section 4.2). Additionally, my replication for other countries (Section 5) is robust to using CompNet data without a firm size cut-off threshold.

[10] I clean my data from the top and bottom two percent outliers with respect to value-added over revenue and revenue over labor, capital, intermediate input expenditures, and labor costs. I eliminate quantity and price information for products' displaying a price deviation from the average product price located in the top and bottom one percent tails.

The data includes information on various productivity and performance measures of firms and other basic information, like firm wages, employment, capital stocks, and sales. In its 8th vintage, the CompNet data also includes information on firms' MRPL and labor market power based on production function estimation techniques. Although this data is aggregated, it collects the distribution of variables within each aggregation level and contains so called "joint-distributions" that summarize variables for given percentiles of other variables. As the CompNet data is population weighted, it is highly representative. The data is available with and without a cut-off rule of 20 employees per firm. I focus on the truncated version, as it is available for more countries (results are robust to using non-truncated data).

A drawback of the CompNet data is its lack of firm-specific price data. Estimates of labor market power and MRPL are thus based on much more assumptions than in my main analysis (see online Appendix C and CompNet (2020)).[11] Besides that, the data features a shorter and by country varying time span. Nevertheless, the CompNet data constitutes a valuable source for testing the external validity of my results. Online Appendix A.2 provides more details on the data and on how to access it.

3 Recovering labor market power expressions

This section derives my framework to estimate firms' labor market power and MRPL. Section 3.1 describes the general setting. Section 3.2 derives the theoretical framework and discusses how labor market power effects wages. Section 3.3 explains how to estimate necessary parameters.

[11] In the CompNet data, I must assume a Cobb-Douglas production function and that firm prices do not vary between firms within an industry. De Loecker et al. (2016) discuss the associated output and input price bias.

3.1 Preliminaries

Firm i produces physical output Q_{it} in period t using the production function:

(1) $$Q_{it} = Q_{it}(.) = Q_{it}(L_{it}, K_{it}, M_{it}, e^{\omega_{it}}).$$

ω_{it} is total factor productivity. L_{it}, K_{it}, and M_{it} respectively denote labor, capital, and intermediate inputs. The only formal requirement for the production function (1) is that it is twice differentiable. To derive firms' labor (or product) market power, we must observe at least one flexible input for which input prices are given to firms. Following the literature, this is M_{it} in my case.[12] In contrast, labor markets can feature any type of market power imperfection. For convenience, I ignore capital market imperfections as they are irrelevant for my analysis.

Labor exists in two types, L_{it}^{MO} and L_{it}^{EB}, with $L_{it}^{MO} + L_{it}^{EB} = L_{it}$, where MO and EB are reminiscent of the monopsonistic (MO) and efficient bargaining (EB) labor market models. L_{it}^{MO} are workers over which firms possess labor market power. L_{it}^{EB} are employees that themselves possesses labor market power. Both labor types are imperfectly substitutable, and firms are characterized by different demand (and supply) for (of) each labor type. There are two wage rates w_{it}^{MO} and w_{it}^{EB}, with w_{it}^{MO} (w_{it}^{EB}) being below (above) the marginal revenue product of L_{it}^{MO} (L_{it}^{EB}).[13]

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[12] This is a standard assumption in the literature on estimating markups following De Loecker & Warzynski (2012). Conditional on this assumption, this allows for intermediate input suppliers charging a markup over marginal costs. Mertens (2020b, online Appendix) validated the assumptions on intermediate inputs using the same data by showing that De Loecker Warzynski (2012) markups derived from firms' energy and raw material input decisions (sub-items of total intermediates) are similar to markup estimates from firms' intermediate input decisions.

[13] I do not specify EB- and MO-workers' characteristics, as my framework does not depend on specific workforce characteristics. For illustration, one could imagine that MO- and EB-workers differ in their outside options, their union membership status, or any other characteristics relevant for labor market power (education, etc.).

In the data, I cannot differentiate between both labor types as I lack information on firms' workforce composition. Therefore, the production function (1) does not differentiate between L_{it}^{MO} and L_{it}^{EB}. Nevertheless, separating labor into L_{it}^{MO} and L_{it}^{EB} in my model is key for i) showing how labor market power can offset existing sources of between-firm wage inequality, ii) offering an intuitive explanation for observing firms paying wages below and above their MRPL, and iii) showing that my estimate of firm labor market power is unbiased under heterogenous workers. The latter allows me to exactly measure *firm-level* labor market power, which is a weighted average of both workforce types' labor market power, from firm-level production and cost data. Although I focus on two labor types, all my derivations extend to a continuum of differentiated workers.

3.2 A framework to calculate labor market power

Consider a bargaining model where risk-neutral EB-workers bargain with profit maximizing firms over rents. In contrast, MO-workers do not bargain with firms. Their wages are a function of firms' MO-labor demand. EB-workers' objective is to maximize wage income taking their outside option $\overline{w}_{it}^{EB}$ as given. This motivates the following Nash problem that EB-workers and firms solve:

$$\text{(2)} \quad \max_{L_{it}^{EB}, L_{it}^{MO}, w_{it}^{EB}, M_{it}, K_{it}} [\phi_{it} \log\left(\left(w_{it}^{EB} - \overline{w}_{it}^{EB}\right)L_{it}^{EB}\right) \\ + \left(1-\phi_{it}\right)\log\left(P_{it}(Q_{it})Q_{it} + w_{it}^{MO}\left(L_{it}^{MO}\right)L_{it}^{MO} - w_{it}^{EB}L_{it}^{EB} - z_{it}M_{it} - r_{it}\,K_{it}\right)].$$

r_{it} and z_{it} are unit input costs for K_{it} and M_{it}. $\phi_{it} \in [0,1]$ denotes EB-workers' bargaining power and P_{it} is firms' output price. This bargaining formulation assumes i) that, in case of a breakdown of negotiations, firms earn zero profits and EB-workers receive their outside option $\overline{w}_{it}^{EB}$ and ii) firms face adjustment frictions preventing a costless replacement of EB-workers.[14] Otherwise, firms would have no incentive to bargain with EB-workers and worker-firm bargaining could not exist in a long-run equilibrium.[15] Hence, adjustment costs are a precondition for worker-side labor market power to exist. Such adjustment frictions result, among others, from unions coordinating their labor supply (McDonald & Solow (1981)) or sunk training costs (e.g. Kline et al. (2019)).

From the first order condition for M_{it}, one can derive firms' markups (μ_{it}):

$$z_{it} = MC_{it}\frac{\partial Q_{it}(.)}{\partial M_{it}} \Leftrightarrow \mu_{it} = \frac{\partial Q_{it}(.)}{\partial M_{it}}\frac{M_{it}}{Q_{it}} * \frac{P_{it}Q_{it}}{z_{it}M_{it}} = \theta_{it}^{M} * \frac{P_{it}Q_{it}}{z_{it}M_{it}}. \tag{3}$$

$MC_{it} = P_{it}/\mu_{it}$ denotes marginal costs and θ_{it}^{X} is the output elasticity of input $X = \{L_{it}^{MO}, L_{it}^{EB}, K_{it}, M_{it}\}$.

From the first order conditions for L_{it}^{MO} and L_{it}^{EB} , we find:

$$w_{it}^{MO}\left(1 + \frac{\partial w_{it}^{MO}}{\partial L_{it}^{MO}}\frac{L_{it}^{MO}}{w_{it}^{MO}}\right) = w_{it}^{MO} \overbrace{\gamma_{it}^{MO}}^{\substack{Wage\ markdown \\ component}} = MRPL_{it}^{MO} \tag{4}$$

and

[14] One can generalize this setting to firms experiencing only a loss in profits instead of a total shutdown of production by defining an outside option for firms. Such an outside option could capture hiring costs or alternative workers being less productive than current EB-workers due to current EB-workers having firm specific human capital. I apply the formulation above because it is much more tractable.

[15] Firm-side adjustment costs are an incremental (often silent) feature underlying *all* models featuring worker-side bargaining power. Labor hoarding models where workers receive a wage above their MRPL produce a related type of labor market power. Although it is intertemporally optimal for the firm to pay workers above their MRPL in these models, it is again the presence of sunk costs in worker skills (experience, training, etc.) that creates adjustment costs and makes labor markets imperfectly competitive. Although, *given these conditions*, the labor hoarding outcome can be optimal for firms, it is still worse from the perspective of firms than a counterfactual situation with perfectly flexible labor markets and without sunk training costs. An equivalent argument can be made for models were workers accept wages below their MRPL to benefit from the reputation of having worked at a well-respected firm. Here, firm labor market power results from firms being differentiated in their reputation and a limited supply of jobs at firms. Firms exploit this situation and pay wages below workers' MRPL. On perfect labor markets, there would instead be an infinite amount of identical firms that bid wages up to workers' MRPL.

$$w_{it}^{EB}\left(1-\frac{\phi_{it}}{1-\phi_{it}}\frac{\pi_{it}}{w_{it}^{EB}L_{it}^{EB}}\right)=w_{it}^{EB}\overbrace{\gamma_{it}^{EB}}^{\substack{Wage\ markup\\ component}}=MRPL_{it}^{EB}. \tag{5}$$

$MRPL_{it}^{MO}$ and $MRPL_{it}^{EB}$ are the marginal revenue products of MO- and EB-employees. π_{it} denotes firm profits. It holds that $\gamma_{it}^{MO}>1$ as $(\partial w_{it}^{MO}/\partial L_{it}^{MO})(L_{it}^{MO}/w_{it}^{MO})>0$ is the inverse labor supply elasticity of MO-type labor. Conversely, $0<\gamma_{it}^{EB}<1$ denotes the part of EB-workers' wages that results from rent sharing, i.e. EB-workers wages exceed their MRPL because they can bargain for a share of firm rents. As wages for EB-workers (MO-workers) are above (below) the marginal revenue product of EB-workers (MO-workers), I call $\gamma_{it}^{MO}$and γ_{it}^{EB} a wage markdown and markup component, respectively.

Now, I show that *firm-level* labor market power is a function of $\gamma_{it}^{MO}$and γ_{it}^{EB}. Multiplying equation (4) with L_{it}^{MO}/Q_{it} and equation (5) with L_{it}^{EB}/Q_{it} gives:

$$\gamma_{it}^{MO}=\frac{\theta_{it}^{L^{MO}}}{\theta_{it}^{M}}\frac{z_{it}M_{it}}{w_{it}^{MO}L_{it}^{MO}} \tag{6}$$

and

$$\gamma_{it}^{EB}=\frac{\theta_{it}^{L^{EB}}}{\theta_{it}^{M}}\frac{z_{it}M_{it}}{w_{it}^{EB}L_{it}^{EB}}, \tag{7}$$

which are firm-labor-type-specific expressions for labor market power. Whereas I do not focus on such worker-type-specific labor market power, equations (6) and (7) can be used by other researchers having access to linked employer-employee data to study firm-worker-type-specific labor market power.

Finally, use $w_{it}^{EB}L_{it}^{EB}+w_{it}^{MO}L_{it}^{MO}=w_{it}L_{it}$ and (6) and (7) to get:

$$w_{it}L_{it}=\frac{\theta_{it}^{L^{MO}}}{\theta_{it}^{M}}\frac{z_{it}M_{it}}{\gamma_{it}^{MO}}+\frac{\theta_{it}^{L^{EB}}}{\theta_{it}^{M}}\frac{z_{it}M_{it}}{\gamma_{it}^{EB}}. \tag{8}$$

Rearranging terms and using (3) gives:

$$\gamma_{it}\equiv\frac{\theta_{it}^{L^{MO}}+\theta_{it}^{L^{EB}}}{\frac{\theta_{it}^{L^{MO}}}{\gamma_{it}^{MO}}+\frac{\theta_{it}^{L^{EB}}}{\gamma_{it}^{EB}}}=\frac{\theta_{it}^{L}}{\theta_{it}^{M}}\frac{z_{it}M_{it}}{w_{it}L_{it}}=\frac{MRPL_{it}}{w_{it}}, \tag{9}$$

because under standard production functions $\theta_{it}^{L^{MO}} + \theta_{it}^{L^{EB}} = \theta_{it}^{L}$.[16] $MRPL_{it}$ denotes the marginal revenue product of firms' total labor and γ_{it} defines firms' total labor market power. If $\gamma_{it} > 1$ ($\gamma_{it} < 1$), wages are below (above) the MRPL and the firm (the firm's workforce) possesses labor market power. As (9) shows, total firm labor market power is a weighted average of firm labor market power over individual worker groups.

In my framework, workers' wages can differ on competitive labor markets ($\gamma_{it} = 1$) due to differences in worker characteristics (e.g. skill). This heterogeneity in worker characteristics creates between-firm wage dispersion, if firms differ in their workforce compositions (and thus their MRPL).[17] To see this, write average wages as:

$$w_{it} = \frac{L_{it}^{EB}}{L_{it}} \frac{MRPL_{it}^{EB}}{\gamma_{it}^{EB}} + \frac{L_{it}^{MO}}{L_{it}} \frac{MRPL_{it}^{MO}}{\gamma_{it}^{MO}} = \frac{MRPL_{it}}{\gamma_{it}}, \tag{10}$$

where even for $\gamma_{it}^{EB} = \gamma_{it}^{MO} = \gamma_{it} = 1$ firm wages can differ due to differences in workforce compositions between firms / worker-firm sorting.

Without this realistic feature, labor market power would always contribute to between-firm wage inequality. The extent to which labor market power can moderate between-firm wage inequality is thus the extent to which it can offset other causes of firm wage differences. Because $w_{it} = MRPL_{it}\gamma_{it}^{-1}$, labor market power moderates between-firm wage inequality, if $MRPL_{it}$ and γ_{it} are positively correlated, which is what I document for the German manufacturing sector and ten other European countries.[18] The existing rent-sharing

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[16] The last identify follows from: $\frac{\theta_{it}^{L}}{\theta_{it}^{M}} \frac{z_{it} M_{it}}{w_{it} L_{it}} = \frac{\frac{\partial Q_{it}(.) L_{it}}{\partial L_{it}\ Q_{it}}}{\frac{\partial Q_{it}(.) M_{it}}{\partial M_{it}\ Q_{it}}} \frac{z_{it} M_{it}}{w_{it} L_{it}} = \frac{\frac{\partial Q_{it}(.) P_{it}}{\partial L_{it}\ \mu_{it}}}{\frac{\partial Q_{it}(.) P_{it}}{\partial M_{it}\ \mu_{it}}} \frac{z_{it}}{w_{it}} = \frac{MRPL_{it}}{MRPM_{it}} \frac{z_{it}}{w_{it}}$. $MRPM_{it} = \frac{P_{it}}{\mu_{it}} \frac{\partial Q_{it}(.)}{\partial M_{it}}$ is the marginal revenue product of intermediate inputs.

[17] The MRPL is a function of product market power, the labor output elasticity, and labor productivity: $MRPL_{it} = \mu_{it}^{-1} * \theta_{it}^{L} * P_{it} Q_{it} / L_{it}$. Hence, if more high-skilled workers cause firms to be more productive, they will receive higher wages than low-skilled workers.

[18] This holds until the point at which high-MRPL firms have such high labor market power that they pay lower wages than low-MRPL firms. Again, this is not the case in the data. High-MRPL firms, which are also highly productive firms, pay significantly higher wages

literature could not document this fact, as it defines *identical* rent-sharing parameters across firms. *By construction*, this creates a hard-wired link between rent-sharing processes (labor market power) and between-firm pay inequality that misinterprets rent-sharing processes (labor market power) as a cause of firm pay differences. From the rent-sharing literature's perspective, my approach can thus be seen as a way to estimate *firm-specific* labor market power (rent-sharing parameters). Online Appendix B provides a numerical example showing that realistically small differences in firms' labor market power/rent-sharing parameters can create the inequality moderating force highlighted in this study.

3.3 Estimation

Before I calculate firms' labor market power and MRPL (equation (9)), I need to recover firms' output elasticities. Therefore, I estimate firms' production function. As the methodology follows previous work, I focus on key aspects and describe the estimation routine in online Appendix C in more detail.

I apply a translog production function allowing for firm- and time-specific output elasticities. The empirical production function writes:

(11) $$q_{it} = \boldsymbol{\phi}_{it}'\boldsymbol{\beta} + \omega_{it} + \varepsilon_{it}.$$

Lower case letters denote logs. $\boldsymbol{\phi}_{it}'$ captures production inputs and their interactions.[19] ε_{it} is an i.i.d. error term. ω_{it} denotes Hicks-neutral productivity and follows a Markov process

(see section 4.2). Note, if a high MRPL results from workers being skilled and raising firms' productivity, then high-MRPL firms must pay larger wages than low-MRPL firms. Else, high-skilled workers will move to low-MRPL firms causing them to become high-MRPL firms. Hence, a positive correlation between firms' MRPL and wages is the only stable equilibrium.

[19] The production function is specified as: $q_{it} = \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} + \beta_{ll} l_{it}^2 + \beta_{mm} m_{it}^2 + \beta_{kk} k_{it}^2 + \beta_{lk} l_{it} k_{it} + \beta_{lm} l_{it} m_{it} + \beta_{km} k_{it} m_{it} + \beta_{lkm} l_{it} k_{it} m_{it} + \omega_{it} + \varepsilon_{it}$. The output elasticity of labor equals: $\frac{\partial q_{it}}{\partial l_{it}} = \beta_l + 2\beta_{ll} l_{it} + \beta_{lm} m_{it} + \beta_{lk} k_{it} + \beta_{lkm} k_{it} m_{it}$.

that firms can influence. Formally, $\omega_{it} = h_{it}(\omega_{it-1}, \boldsymbol{T}_{it-1}) + \xi_{it} = h_{it}(.) + \xi_{it}$, where ξ_{it} denotes the innovation in productivity and $\boldsymbol{T}_{it} = (EX_{it}, NumP_{it})$ captures firm actions influencing productivity. EX_{it} and $NumP_{it}$ denote firms' export status and number of products. I thus allow for (dis)economies of scope and learning from export market participation to affect productivity. Whereas ω_{it} is unobserved to the econometrician, firms know ω_{it} before making their input decisions for flexible inputs (intermediates). I assume that labor and capital do not respond to productivity shocks, which is motivated by Germany's inflexible labor market setting (OECD (2018)).[20]

There are three identification issues preventing a direct estimation of equation (11) by OLS. First, firms' intermediate input decisions depend on unobserved realizations of ω_{it}. Second, the production function (11) specifies a physical production model. Yet, while I observe firms' physical output, I cannot aggregate it across various products of multi-product firms (e.g. kilograms of vegetables vs. liters of beverages). Third, I do not observe *input* prices for all production inputs. If input prices are correlated with input decisions and output levels, this causes another endogeneity problem.

Online Appendix C details how I address these identification issues. In summary: I address the endogeneity problem resulting from the dependence of firms' flexible input decision on realization of ω_{it} by applying a control function approach to control for unobserved productivity following Olley & Pakes (1996). To address the issue that output quantities cannot be aggregated within multi-product firms, I calculate a firm-specific output price index as in Eslava et al. (2004). I use this price index to deflate observed firm revenue (for all firms), which purges it from price variation (I keep using q_{it} for the resulting quasi-quantities). Finally, to account for unobserved input prices, I follow De Loecker et al. (2016)

[20] This is consistent with labor being more flexible than capital. These timing assumptions are consistent with other studies (e.g. De Loecker et al (2016)). My results hold when allowing labor to respond to productivity shocks.

and define a price control function from firms' observed output prices and market shares to control for unobserved input price variation. The latter assumes that output prices are informative about input prices.

After implementing these procedures, the production function contains two additional control functions, one for unobserved productivity ($h_{it}(.)$) and one for unobserved input prices ($B_{it}(.)$):

(12) $$q_{it} = \tilde{\boldsymbol{\phi}}'_{it}\boldsymbol{\beta} + B_{it}(.) + h_{it}(.) + \xi_{it} + \varepsilon_{it}.$$

$\tilde{\boldsymbol{\phi}}_{it}$ contains the same input terms as $\boldsymbol{\phi}'_{it}$, either deflated by an industry-deflator (capital and intermediates) or reported in true quantities (labor). The tilde highlights that some inputs do not enter in true quantities. The latter is precisely the reason for introducing the input price control function, $B_{it}(.)$, which controls for firm price variation and is a flexible function of output prices, product market shares, firm location, and firms' four-digit industry classification. Finally, $h_{it}(.) = \omega_{it} - \xi_{it}$, is a control function for productivity based on a firm's inverted demand function for raw materials and energy inputs.

I estimate (12) separately by two-digit sectors and jointly form identifying moments on $\xi_{it} + \varepsilon_{it}$ as in Wooldridge (2009). As mentioned, I discuss the entire approach and its assumptions in online Appendix C. Estimated average (median) output elasticities across all firms equal 0.64 (0.63) 0.30 (0.30) 0.11 (0.11) respectively for intermediate, labor, and capital inputs (online Appendix C). To ensure that I can compare statistics across firms, I only keep firms for which I can compute labor market power and marginal revenue products of labor. My final sample consists of 242,982 firm-year observations for which online Appendix A.1 summarizes key statistics.

4 Results

This section shows my empirical results. Section 4.1 compares the wage and MRPL distribution over time and concludes that labor market power contributed to between-firm wage equality. Section 4.2 highlights that the key mechanism for this finding is that large, high-paying, high-MRPL firms posses the highest degree of labor market power and thus pay wages below MRPL. Section 5 will discuss the role of measurement error, adjustment costs, and characteristics of the German manufacturing sector in driving my results.

4.1 Wage distribution and marginal revenue products

DISTRIBUTION OF MARGINAL REVENUE PRODUCTS OF LABOR AND WAGES ACROSS FIRMS

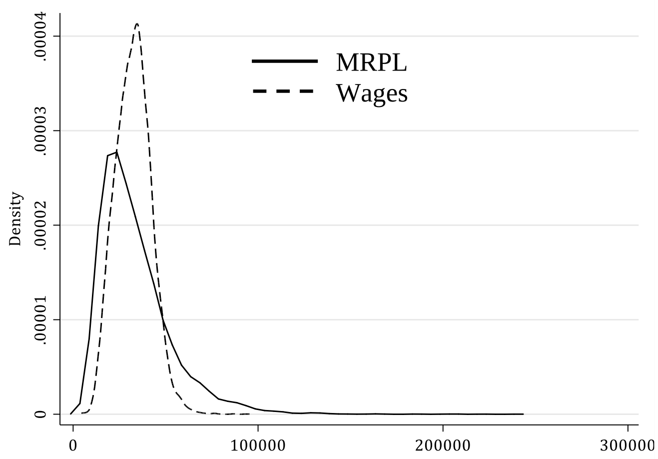

FIGURE 1 – Distribution of marginal revenue products of labor and average wages across firms in 1995. Results for other years look similar. Expressed in values of 1995. Germany's manufacturing sector. Sample firms.

Figure 1 shows the firm wage and MRPL distributions for the German manufacturing sector, documenting that MRPL dispersion exceeds wage dispersion. As wages are a function of firms' MRPL and labor market power, wages would equal the MRPL in every firm on competitive labor markets. Holding marginal revenue products constant, the competitive wage distribution ($\gamma_{it} = 1$) would thus be much more dispersed than observed in the data. This even holds if firms' marginal products decline in labor (i.e. if the MRPL distribution changes when adjusting wages). In that case, if firms adjust their labor inputs while moving from the factual case with labor market power to the counterfactually competitive labor market scenario, the MRPL and wage distributions will move towards each other, leading to a larger between-firm wage dispersion than observed in the data.[21] Labor market power therefore contributes to between-firm wage equality.

Table 1 shows qualitatively the same result within each two-digit manufacturing industry of my analysis. MRPL dispersion exceeds wage dispersion in almost every industry, sometimes by a factor of more than two. Table 1 also displays industry statistics for labor market power. As labor market power creates a wedge between firms' wages and MRPL, high (low) labor market power firms are too small (large) from an efficiency perspective. The extent of labor market power dispersion is thus a direct measure of misallocation (as in Hsieh & Klenow (2009)). Labor market power dispersion is on average larger in sectors in which wage and MRPL dispersion differ the most, highlighting a potential trade-off between the moderating effect of labor market power on firm pay differences and allocative efficiency. As I show below, this mostly results from large, high-paying, and high-MRPL firms having large and growing labor market power due to paying relatively high wages that are still far below their MRPL. This makes these firms inefficiently small, although they are already large.

Figure 2, Panel A shows how between-firm dispersion in wages and MRPL changed within the German manufacturing sector between 1995 and 2016. Over these years, between-firm dispersion in wages and MRPL, measured by the standard deviation (90-10 percentile difference), increased by 24% (25%) and 26% (18%), reflecting an absolute increase of 2,300€ (6,100€) and 5,000€ (7,800€) in values of 1995, respectively.

[21] To see this, consider a firm with labor market power. Assume that the returns to the firm from employing labor (MRPL) are declining in labor. Moving to competitive labor markets will increase wages. This increases the supply of labor and the equilibrium workforce of the firm. As the MRPL declines in labor, the MRPL will be smaller under competitive markets and wages will be higher.

TABLE 1

DISPERSION IN WAGES, MARGINAL REVENUE PRODUCTS OF LABOR, AND LABOR MARKET POWER, BY TWO-DIGIT INDUSTRY

		Wages			Marginal revenue products of labor			Labor market power		
	Obs.	Median	Sd.	Percentile diff. (90-10)	Median	Sd.	Percentile diff. (90-10)	Median	Sd.	Percentile diff. (90-10)
Sector		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
15 Food products and beverages	29,455	23,003€	10,882€	27,634€	14,832€	10,999€	25,727€	0.66	0.28	0.67
17 Textiles	8,369	28,254€	8,721€	21,683€	30,288€	9,938€	25,729€	1.11	0.32	0.77
18 Apparel, dressing, and dyeing of fur	3,200	23,932€	8,096€	20,003€	17,129€	10,641€	19,102€	0.77	0.32	0.68
19 Leather and leather products	1,811	25,030€	7,326€	19,393€	20,943€	11,045€	24,511€	0.88	0.36	0.85
20 Wood and wood products	6,766	29,310€	7,923€	20,380€	22,637€	20,302€	48,932€	0.85	0.57	1.36
21 Pulp, paper, and paper products	6,693	34,710€	9,127€	23,669€	35,319€	22,475€	53,354€	1.08	0.48	1.20
22 Publishing and printing	5,928	34,172€	10,305€	26,758€	21,677€	15,966€	35,088€	0.69	0.40	0.91
24 Chemicals and chemical products	14,851	40,818€	12,468€	31,713€	45,185€	28,334€	68,519€	1.10	0.63	1.47
25 Rubber and plastic products	15,844	31,420€	8,772€	22,483€	24,506€	15,267€	32,786€	0.84	0.37	0.85
26 Other non-metallic mineral products	13,286	33,637€	9,177€	23,388€	34,948€	18,502€	47,909€	1.06	0.45	1.10
27 Basic metals	9,587	38,252€	9,196€	24,201€	48,759€	33,553€	78,561€	1.32	0.70	1.67
28 Fabricated metal products	32,795	32,964€	8,972€	22,538€	27,189€	15,756€	36,472€	0.88	0.39	0.95
29 Machinery and equipment	40,070	38,616€	10,146€	25,943€	38,130€	21,462€	49,170€	1.01	0.44	1.03
30 Electrical and optical equipment	1,980	37,885€	11,871€	29,462€	33,071€	37,302€	65,316€	0.92	0.84	1.52
31 Electrical machinery and apparatus	14,772	33,881€	10,542€	27,306€	29,822€	23,209€	50,996€	0.92	0.54	1.22
32 Radio, television, and communication	4,338	33,683€	12,233€	30,052€	38,495€	32,500€	63,553€	1.17	0.74	1.50
33 Medical and precision instruments	10,534	35,088€	12,449€	31,986€	33,975€	31,918€	71,396€	0.96	0.68	1.46
34 Motor vehicles and trailers	8,412	34,919€	10,561€	26,467€	38,065€	30,079€	52,497€	1.14	0.54	1.14
35 Transport equipment	2,549	31,510€	8,429€	21,591€	26,176€	9,476€	24,634€	0.81	0.35	0.88
36 Furniture manufacturing	11,742	29,395€	8,498€	21,825€	24,848€	13,918€	31,477€	0.91	0.39	0.91
Across all industries	242,982	33,211€	11,091€	28,284€	29,650€	23,301€	50,401€	0.93	0.51	1.13

Notes: Table 1 reports medians, standard deviations, and 90-10 percentile differences for wages, marginal revenue products of labor, and labor market power. Wages and marginal revenue products of labor are expressed in values of 1995. Germany’s manufacturing sector. Sample firms.

BETWEEN-FIRM WAGE AND MRPL DISPERSION, OVER TIME

Panel A: Firm wage and MRPL dispersion

Panel B: Differences between firm wage and MRPL dispersion

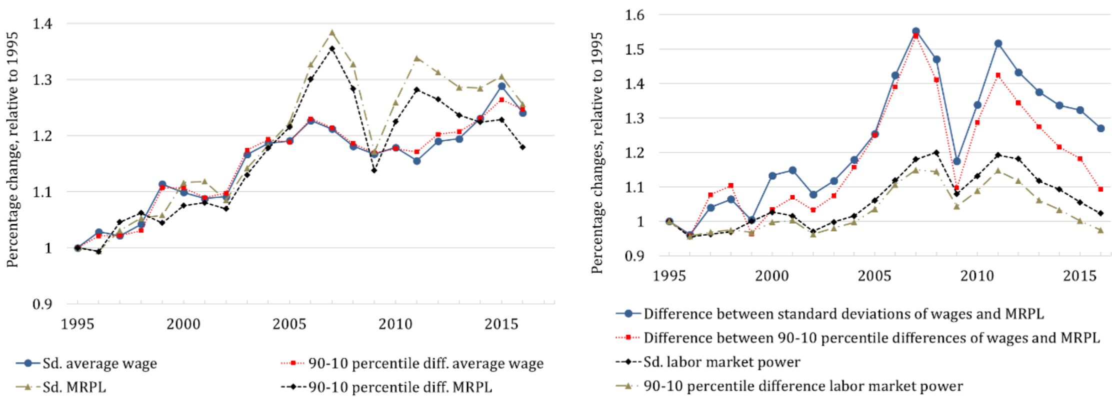

FIGURE 2 – Panel A: Standard deviations and 90-10 percentile differences for firms' wages and marginal revenue products of labor. Panel B: Differences between standard deviations and 90-10 percentile differences for firms' wages and marginal revenue products of labor together with the standard deviation and 90-10 percentile difference of labor market power. Values are normalized to unity in 1995. Germany's manufacturing sector. Sample firms.

As, relative to wage dispersion, the level of MRPL dispersion is larger, the percentage wise similar increase in MRPL and wage dispersion implies a widening of the gap between MRPL and wage dispersion levels. Figure 2, Panel B illustrates this by plotting *level differences* between wage and MRPL dispersion. The documented upward trends imply that MRPL dispersion became larger over time compared to wage dispersion. The latest decrease in the difference between wage and MRPL dispersion reflects an increase in between-firm wage inequality. Here, wage dispersion catches up with the growth of MRPL dispersion.

Figure 2, Panel B shows that dispersion in labor market power displayed only a slight upward trend in past decades. This is because firms labor market power is defined as the *ratio* (not the difference) between wages and the MRPL. Nevertheless, as MRPL dispersion increases stronger than wage dispersion in terms of Euro levels, there is an increasingly strong moderating effect of labor market power on the increase in between-firm wage inequality over time. Under competitive labor markets, wage inequality between firms would thus have grown stronger.

TABLE 2

SELECTED PERCENTILE DIFFERENCES FOR FIRM WAGES AND MARGINAL REVENUE PRODUCTS OF LABOR OVER TIME, ENTIRE MANUFACTURING SECTOR

Year	Percentile differences firm wages			Percentile differences firm MRPL			Diff. between column 4 and 1
	90-10	90-50	50-10	90-10	90-50	50-10	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1995	24,525€	12,041€	12,484€	43,502€	28,724€	14,778€	18,977€
2000	27,148€	13,492€	13,656€	46,775€	31,247€	15,528€	19,628€
2005	29,141€	14,766€	14,375€	52,861€	35,763€	17,098€	23,720€
2010	28,869€	15,641€	13,228€	53,292€	36,991€	16,302€	24,423€
2016	30,578€	16,687€	13,891€	51,321€	35,037€	16,284€	20,743€

Notes: Table 2 reports 90-10, 90-50, and 50-10 percentile differences of the firm distribution for wages and marginal revenue products of labor. Wages and marginal revenue products of labor are expressed in values of 1995. Germany's manufacturing sector. Sample firms.

Table 2 shows that most of the increase in wage and MRPL dispersion occurs in the upper part of the distributions. For wages, the 90-50 percentile difference was even below the 50-10 difference in 1995. Over time, however, the former increased from 12,000€ to 16,500€, whereas the 50-10 percentile difference only increased from 12,500€ to 14,000€ (in values of 1995). For the MRPL distribution, the importance of the upper half of the distribution in explaining the increase in MRPL dispersion is even larger. Firms at the upper ends of the wage and MRPL distributions have thus a significant role in explaining the observed increase in wage and MRPL dispersion.

Table 3 documents a strong increase in wage and MRPL dispersion also within narrow four-digit industries and German federal states (Germany consists of 16 federal states). Table 3 shows selected year coefficients from regressing percentile differences from the wage and MRPL distributions on a full set of year and four-digit industry (federal state) dummies using OLS were 1995 is the baseline category. The coefficients for the year dummies reflect the average change in percentile differences within four-digit industries and within regions between 1995 and the reported year.

TABLE 3

SELECTED PERCENTILE DIFFERENCES FOR FIRM WAGES AND MARGINAL REVENUE PRODUCTS OF LABOR OVER TIME, WITHIN FOUR-DIGIT INDUSTRIES AND FEDERAL STATES.

Panel A: Within four-digit industries

Coefficient on year dummies	Percentile differences firm wages			Percentile differences firm MRPL			Diff. column 4 and 1
	90-10	90-50	50-10	90-10	90-50	50-10	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2000	795.1€ (339.2€)	662.8€ (259.2€)	132.4€ (245.6€)	2,660€ (925.0€)	2,506€ (802.9€)	154.0€ (409.9€)	1,864.9€
2005	2,674€ (336.3€)	1,937€ (260.3€)	737.1€ (259.0€)	5,730€ (911.8€)	4,167€ (841.2€)	1,562€ (365.9€)	3,056.0€
2010	2,481€ (342.7€)	2,600€ (283.1€)	-118.9€ (237.0€)	6,982€ (1,062€)	6,049€ (951.9€)	932.9€ (370.3€)	2,481.0€
2016	2,597€ (370.0€)	2,662€ (306.0€)	-65.32€ (257.4€)	5,688€ (1,113€)	5,181€ (1,048€)	506.8€ (373.5€)	3,091.0€

Panel B: Within federal states

Coefficient on year dummies	Percentile differences firm wages			Percentile differences firm MRPL			Diff. column 4 and 1
	90-10	90-50	50-10	90-10	90-50	50-10	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2000	3,811€ (804.1€)	2,700€ (703.8€)	1,111€ (294.5€)	3,292€ (1,342€)	2,565€ (1,354€)	727.9€ (507.7€)	-519.0€
2005	5,794€ (379.5€)	2,996€ (352.6€)	2,798€ (283.4€)	10,566€ (1,393€)	7,997€ (1,283€)	2,569€ (438.4€)	4,772.0€
2010	5,626€ (579.0€)	3,835€ (369.5€)	1,791€ (379.0€)	11,633€ (1,339€)	9,593€ (1,204€)	2,040€ (396.7€)	6,007.0€
2016	6,709€ (943.1€)	4,391€ (513.1€)	2,318€ (548.3€)	9,344€ (1,169€)	7,930€ (1,062€)	1,415€ (513.1€)	2,635.0€

Notes: Table 3 reports coefficients and standard errors from regressions of 90-10, 90-50, and 50-10 percentile differences on a full set of year dummies and either a full set of four-digit industry dummies (Panel A) or a full set of federal state dummies (Panel B). The coefficients report the average changes in percentile differences within four-digit industries (Panel A) or federal states (Panel B), relative to the base year 1995. Columns 1-3 show percentile differences for firm wages. Columns 4-6 show percentile differences for firms' marginal revenue products of labor. Standard errors are reported in parentheses and clustered at the four-digit industry (Panel A) or federal state (Panel B) level. Euro values of 1995. Germany's manufacturing sector. Sample firms.

The coefficients on 2016 indicate that the 90-10 percentile difference for firm wages and marginal revenue products of labor increased by 2,600€ and 5,700€ within four-digit industries (Panel A) and by 6,700€ and 9,300€ within federal states (Panel B), respectively.[22] As the increase in MRPL dispersion is much larger than the increase in wage dispersion, firm heterogeneities in labor market power moderated the increase in between-firm wage inequality also within narrow industries and regions.

[22] In terms of standard deviations, wage and MRPL dispersion increased by 1,100€ and 2,900€ within four-digit industries and 2,800€ and 5,400€ within federal states.

Consistent with evidence on the entire manufacturing sector, Table 3 shows that also within four-digit industries and regions, wage and MRPL dispersion mostly grew due to a widening of 90-50 percentile differences. Changes in the upper parts of these distributions were several times larger than changes in the corresponding 50-10 percentile differences. The next section investigates this key role of the upper percentiles in more detail.

4.2 The role of high-paying, large, and high-MRPL firms

Table 4 reports averages for wages, marginal revenue products of labor, labor productivity (log of value-added over employment, denoted by "labor prod."), firms' product market power/markups (calculated from equation (4), denoted by PMP), and firms' labor market power (LMP) for ventiles of the firm employment, wage, and MRPL distributions (I divide each distribution into twenty equally sized parts).

In addition to highlighting the strong persistence of firms' MRPL being much more dispersed than firms' wages, Table 4 provides several key insights. First, note that for most of the wage distribution, marginal revenue products of labor are close to wages. Just after the 70^{th} percentile of the wage distribution, the wedge between wages and marginal revenue products widens and increases further when moving to the top ventiles (columns 1 and 2). Similarly, except for the first ventile, firm labor market power stays around unity until the 70^{th} percentile. The further we move beyond the 70^{th} percentile, the larger the average degree of firms' labor market power. Labor market power is thus concentrated in high-paying firms. The latter is in line with existing evidence i) suggesting that high-paying firms can lower wages and create rents by hiding behind industry-wide wage standards (Hirsch & Mueller (2020)) and ii) documenting for specific occupational fields that firms exert labor market power particularly over high-paid workers.[23] Notably, product market power, while slightly increasing, stays on similar levels along the wage distribution.

Looking at the firm size and MRPL distributions, I find that small and low-MRPL firms pay low wages that are below marginal revenue products of labor. This implies that employees possess themselves labor market power within these firms (columns 6, 7, 11, and 12).[24] Moving to upper ventiles, wages and marginal revenue products become larger. Slightly above the median of both distributions, marginal revenue products exceed wages, eventually becoming much larger than wages at the top ventiles. Accordingly, firms' labor market power steadily grows along the firm size and MRPL distributions, reaching extreme values for the largest and highest-MRPL firms. The positive association between size and marginal revenue products of labor highlights the exceptional productivity of large firms. This is because, holding productivity constant, firms' MRPL decreases in the number of employees, whereas higher firm productivity levels shift up a firm's MPRL for a given firm size.[25]

[23] Goolsbee & Syverson (2019) show that universities and four-year-colleges exert high monopsony power over their tenure track faculty (as opposed to their non-tenure track faculty). Gibson (2020) shows that non-compete agreements among Silicon Valley technology firms led to a considerable decline in wages for affected workers.
[24] Note that these firms have comparably high markups, explaining why workers in these firms can bargain for a share of rents (i.e. without positive markups there will be no product market rents to share).
[25] Characteristics along firm productivity ventiles look similar to the characteristics along distributions reported in Table 4.

TABLE 4

WAGES, MARGINAL REVENUE PRODUCTS OF LABOR, PRODUCTIVITY, AND PRODUCT AND LABOR MARKET POWER, FOR FIRM VENTILES OF THE FIRM WAGE, SIZE, AND MRPL DISTRIBUTIONS

	Mean values for firm wage ventiles					Mean values for number of employees ventiles					Mean values for MRPL ventiles				
	Wage	MRPL	Labor prod.	PMP	LMP	Wage	MRPL	Labor prod.	PMP	LMP	Wage	MRPL	Labor prod.	PMP	LMP
Ventiles (P = percentile)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Firms ≤ 5P	13,487€	12,296€	9.78	1.02	0.92	29,051€	19,423€	10.36	1.13	.69	18,510€	7,973€	9.97	1.19	.49
Firms > 5P and ≤ 10P	17,899€	17,320€	10.02	1.04	0.97	28,957€	21,263€	10.37	1.13	.75	22,610€	11,957€	10.14	1.16	.59
Firms > 10P and ≤ 15P	20,768€	20,900€	10.18	1.05	1.01	29,139€	22,462€	10.37	1.12	.79	25,549€	14,734€	10.28	1.16	.63
Firms > 15P and ≤ 20P	22,950€	23,099€	10.27	1.06	1.01	29,593€	23,604€	10.40	1.11	.82	26,855€	16,902€	10.3	1.14	.69
Firms > 20P and ≤ 25P	24,841€	24,720€	10.34	1.07	1.00	30,019€	24,661€	10.41	1.11	.84	28,241€	18,876€	10.35	1.14	.73
Firms > 25P and ≤ 30P	26,535€	26,362€	10.39	1.08	.99	30,590€	25,876€	10.45	1.11	.86	29,212€	20,734€	10.40	1.13	.77
Firms > 30P and ≤ 35P	28,121€	27,751€	10.45	1.08	.99	30,679€	27,155€	10.45	1.10	.90	30,060€	22,574€	10.45	1.12	.81
Firms > 35P and ≤ 40P	29,625€	29,197€	10.49	1.09	.99	31,405€	28,497€	10.48	1.10	.92	31,063€	24,450€	10.47	1.11	.84
Firms > 40P and ≤ 45P	31,069€	30,278€	10.53	1.10	.98	31,580€	29,959€	10.50	1.09	.96	32,033€	26,421€	10.51	1.11	.88
Firms > 45P and ≤ 50P	32,476€	32,130€	10.55	1.10	.99	31,950€	31,058€	10.52	1.09	.98	32,890€	28,565€	10.53	1.09	.93
Firms > 50P and ≤ 55P	33,885€	33,607€	10.62	1.10	.99	32,551€	32,402€	10.54	1.09	1.00	33,815€	30,832€	10.58	1.09	.97
Firms > 55P and ≤ 60P	35,311€	35,707€	10.66	1.10	1.01	33,254€	34,488€	10.57	1.08	1.04	34,663€	33,285€	10.60	1.08	1.02
Firms > 60P and ≤ 65P	36,741€	37,226€	10.70	1.11	1.01	33,420€	35,818€	10.57	1.08	1.08	35,576€	35,977€	10.64	1.07	1.07
Firms > 65P and ≤ 70P	38,232€	39,221€	10.74	1.11	1.03	34,276€	38,138€	10.61	1.07	1.12	36,824€	39,020€	10.69	1.07	1.12
Firms > 70P and ≤ 75P	39,830€	41,727€	10.78	1.11	1.05	35,151€	41,061€	10.64	1.07	1.17	37,927€	42,572€	10.72	1.05	1.18
Firms > 75P and ≤ 80P	41,580€	44,544€	10.81	1.11	1.07	36,156€	43,745€	10.65	1.06	1.21	39,372€	46,748€	10.75	1.04	1.25
Firms > 80P and ≤ 85P	43,639€	48,726€	10.86	1.11	1.12	37,828€	47,354€	10.70	1.06	1.26	40,869€	52,008€	10.81	1.03	1.34
Firms > 85P and ≤ 90P	46,147€	52,944€	10.91	1.11	1.15	39,619€	51,719€	10.76	1.06	1.30	42,510€	59,315€	10.89	1.02	1.47
Firms > 90P and ≤ 95P	49,707€	59,281€	10.97	1.11	1.19	40,937€	57,374€	10.76	1.05	1.39	44,662€	70,791€	11.01	1.00	1.66
Firms > 95P	58,394€	69,974€	11.09	1.11	1.20	45,379€	72,207€	10.90	1.03	1.58	47,986€	103,307€	11.12	.97	2.23
Overall average	33,560€	35,348	10.55	1.09	1.03	33,560€	35348€	10.55	1.09	1.03	33,560€	35,348€	10.55	1.09	1.03
Total observations	242,982	242,982	222,215	242,982	242,982	242,982	242,982	222,215	242,982	242,982	242,982	242,982	222,215	242,982	242,982

Notes: Table 4 reports averages for wages, marginal revenue products of labor, labor productivity, firms' product market power, and firms' labor market power for each ventile the firm wage, size (employment), and MRPL distributions. Wages and marginal revenue products of labor are expressed in values of 1995. Germany's manufacturing sector. Sample firms.

Across all distributions, the top ends are characterized by high MRPL-wage differences that are multiple times higher than respective MRPL-wage gaps at the bottom ends of the distributions. MRPL-wage differences in high-paying, large, and high-MRPL firms are thus the main reason for why the MRPL distribution is more dispersed than the wage distribution. As consequence, the extreme labor market power of top firms heavily contributes to between-firm wage equality.

Finally, note that highly productive firms are large, pay high wages, and have high marginal revenue products of labor (columns 3, 6, and 9). Furthermore, product market power is less dispersed than labor market power and falls with firms' size and MRPL, while it slightly grows with wages. This is consistent with i) high product market power firms being forced to share rents with their workforce (Nickell (1999)) and ii) large firms expanding their product mix into competitive product markets (e.g. predatory pricing), while generating most of their rents from labor markets. The extreme labor market power, compared to low product market power levels, of large, high-paying, and high-MRPL firms offers an appealing explanation for the success of these firms: Although such "superstar firms" pay high wages, the return on their workers is larger. This allows these "superstars" to create high labor market rents and to be profitable despite selling on competitive product markets.

Figures 3 and 4 show that the key role of large, high-wage, and high-MRPL firms in contributing to wage and MRPL dispersion grows over time. Both figures plot changes in wages, MRPL, and labor market power for the bottom and top ventiles of the wage, size, and MRPL distributions. Panel A and B of Figure 3 show that wages and marginal revenue products of labor steadily grew for the top ventiles, while they stayed constant or slightly declined for the bottom ventile firms. Again, marginal products grew stronger than wages for the top ventiles. Figure 4 shows that there is even a slightly increasing labor market power trend for top ventile firms. Recap, even a stable trend in labor market power implies a widening of MRPL-wage gaps in these firms. The slight upward trend in labor market power for top firms thus implies a strong increase in their labor market rents.[26]

FIRM WAGES AND MRPL OVER TIME FOR TOP AND BOTTOM VENTILE FIRMS

Panel A: Firm wages over time

Panel B: Firm MRPL over time

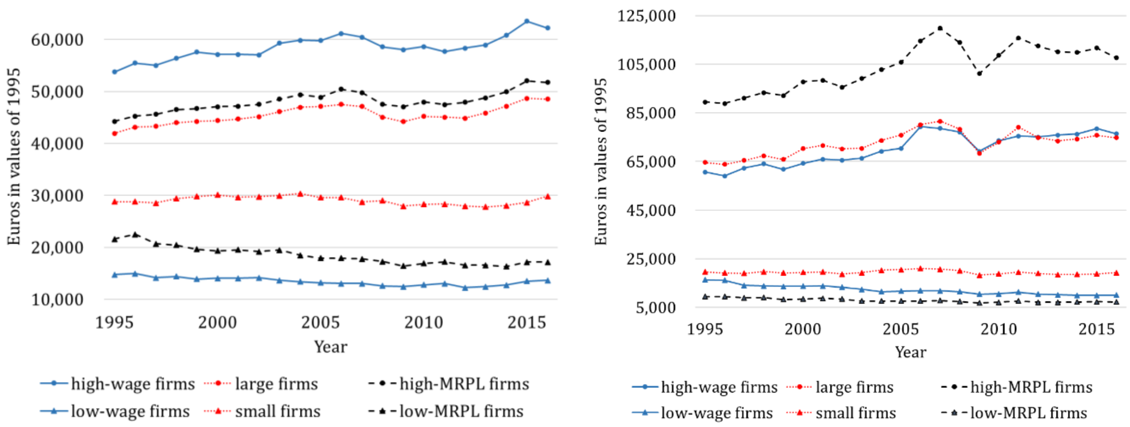

FIGURE 3 – Average firm wages and MRPL over time for the top and bottom ventiles of the firm wage, size, and MRPL distributions. Germany's manufacturing sector. Sample firms.

LABOR MARKET POWER OVER TIME FOR TOP AND BOTTOM VENTILE FIRMS

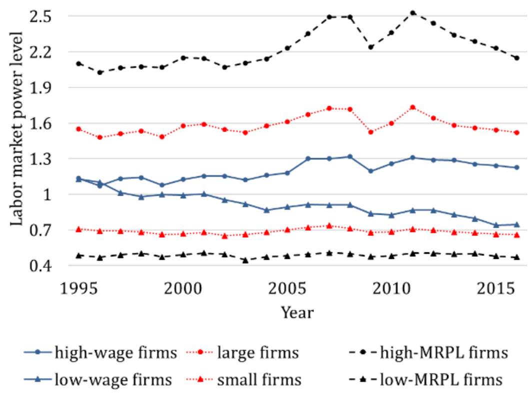

FIGURE 4 – Average labor market power over time for the top and bottom ventiles of the firm wage, size, and MRPL distributions. Germany's manufacturing sector. Sample firms.

In contrast, bottom ventile firms show a stable or even declining labor market power trend. This can be seen most clearly from comparing high- and low-wage firms in Figure 4.

[26] Online Appendix F shows that product market power in these top firms, although increasing, remained on comparably competitive levels.

Both firm types had equal labor market power levels in 1995. Yet, high-wage firms significantly increased their labor market power, while low-wage firms' labor market power strongly declined over time. Although wages departed for both groups, the differential evolution of high- and low-wage firms' labor market power alleviated the increase in firm wage differences over the past decades.

5 Discussion and replication for other countries

5.1 Measurement error: discussion and alternative estimates

My estimation of the MRPL is based on a complex production function estimation routine. Hence, there might be concerns about measurement error causing MRPL dispersion to be larger than wage dispersion. As my results are driven by the right tails of the firm wage, size, and MRPL distributions, any measurement error relevant for explaining my findings would need to create an upward bias in labor market power for the upper parts of these distributions. Hence, my results cannot be driven by statistical noise.

It is also unlikely that adjustment costs *unrelated* to labor market power drive my results because MRPL-wage differences are larger in top firms and grow over time. Particularly, growing labor or skill shortage cannot explain the increase in measured labor market rents at top firms because it is well-documented that, for Germany, skill shortage is lowest for the largest firms and that large firms generate sufficiently high profits to pay higher wages, which could raise labor supply (Dettman et al. (2019)). Finally, my findings are consistent with recent evidence showing that firms exert high labor market power over high-paid workers (Goolsbee & Syverson (2019); Gibson (2020); Bachmann et al. (2020)), providing support for an inequality-moderating effect of labor market power in high-wage segments. Also numerically, measurement error would need to be unrealistically high to compensate MRPL-wage differences at top firms that drive my results. Depending on the distribution (wages, employment, or MRPL) average marginal revenue products of labor exceed average wages by 15% to 215% in the top three ventiles.

Nevertheless, to provide some robustness analysis, I replicate core results using a much simpler Cobb-Douglas specification and ii) a time-varying version of my baseline translog production model that estimates production function coefficients separately by years in online Appendix E. The latter specification also accounts for industry-level biased technological change that affects the relative marginal products of input factors as it allows the coefficients of the production function to vary over time (De Loecker et al. (2020)). My results hold for both robustness checks.

5.2 Replication for other countries

Another concern could be that factors specific to the German manufacturing sector drive my results. For instance, the German manufacturing sector is characterized by a high coverage of industry-level bargained wage standards. This might cause the wage distribution to be narrower than in other sectors and countries and might be one factor creating labor market power. To test for the external validity of my results, I replicate key findings for ten other European countries using the CompNet data.[27] As mentioned, the CompNet data includes information on almost all economic sectors (see online Appendix A.2). Therefore, the results below are not subject to any sector specificities.

[27] I exclude the years 2001-2003 for Denmark due to changes in variable definitions leading to extreme outliers.

TABLE 5

MRPL AND FIRM WAGE DISPERSION IN SEVERAL EUROPEAN COUNTRIES

Country	Years (1)	Average firm wage (2)	90-10 percentile differences, wage distribution (3)	90-10 percentile differences, MRPL distribution (4)	Time trend of differences between MRPL and wage dispersion (5)
Italy	2006-2019	30,676.12€	28,296.22€	64,539.35€	-1,320.67*** (225.01)
Spain	2008-2018	28,176.89€	26,296.81€	66,736.65€	-147.62 (264.10)
Belgium	2000-2018	39,470.57€	32,338.87€	82,421.75€	482.81*** (143.82)
Slovenia	2002-2019	25,414.64€	22,323.28€	53,789.52€	556.94*** (103.24)
Poland	2002-2019	16,750.54€	19,840.09€	36,673.02€	302.05*** (38.33)
Croatia	2002-2019	14,171.30€	15,681.26€	70,533.57€	-1,386.22*** (241.19)
Denmark	2004-2016	29,565.18€	33,534.12€	101,603.2€	-1,185.22 (874.48)
Finland	1999-2019	29,548.92€	23,098.78€	55,550.73€	-559.51*** (84.22)
Sweden	2003-2019	37,512.13€	32,146.18€	14,9761.3€	-1,222.56** (516.85)
Switzerland	2009-2018	53,517.75€	44,752.45€	66,230.91€	53.64 (272.01)

Notes: Table 5 shows MRPL and firm wage dispersion for several European countries. Column (1) reports the years of observation, column (2) reports the average firm wage and column (3) and (4) respectively show average 90-10 percentile differences for firms' wages and MRPL across all years (values of 2005, PPP deflated). Column (5) reports the coefficient from a regression of the difference in wage and MRPL dispersion (column (4) minus column (3) for every year) on a linear time trend. Robust standard errors for column (5) are reported in parentheses. Significance: *10 percent, **5 percent, ***1 percent. CompNet data.

Table 5 shows country-level average 90-10 percentile differences for wage and MRPL distributions for several European countries.[28] In every country of the sample, MRPL dispersion exceeds wage dispersion. Hence, in all countries, labor market power contributes to between-firm wage *equality*.

Column 4 shows coefficients from a regression of the difference between MRPL and wage dispersion on a linear time trend. A positive coefficient implies that MRPL dispersion grows stronger than wage dispersion, implying that the moderating effect of labor market power on firm pay differences increases over time. Results are more mixed with respect to this analysis. In Italy, Croatia, Finland, and Sweden the inequality moderating effect of labor market power decreases over time, whereas in Belgium, Slovenia, and Poland, it became stronger in past years. Results for Spain, Denmark, and Switzerland are inconclusive. Yet, in

[28] MRPL and labor market power estimates are directly available in the CompNet data. The estimates I use are based on Cobb-Douglas production functions estimated by OLS. Although the CompNet data contains also more sophisticated estimates, the Cobb-Douglas OLS specifications are the only ones available in the joint-distributions statistics used in Table 6 below (due to high data requirements of the other specifications). Results of Table 5 are robust to using the more sophisticated production function estimates, including a translog specification estimated by a control function approach as in Ackerberg et al. (2015).

all countries, MRPL dispersion exceeds wage dispersion in every year of the data (see also online Appendix G). Hence, there is a persistent inequality moderating effect of labor market power in all ten countries.

Table 6 replicates key results from Table 4 for my set of European countries using the “joint distributions” from the CompNet data. These “joint distributions” report median values of several variables by deciles of another variable’s distribution. To condense my analysis for multiple countries, I run the following regressions:

(13) $$\bar{y}_{ndt} = \beta_{decile\_x} decile\_x_{ndt} + \upsilon_t$$

where $\bar{y}_{ndt} = \{LMP, PMP, firm\ wage, MRPL,\}$ is the median value of a variable of interest and $decile\_x_{ndt} = \{1,2,\ldots,10\}$ denotes deciles, d, of the distribution of $x = \{wage, MRPL, size, labor\ productivity\}$ in country n and year t. υ_t is a year fixed effect. The coefficients β_{decile_x}, which I report in Table 6, give the percentage increase in $\bar{y}_{ndt}$ when moving up one decile of the distribution of x.

Results are consistent with evidence for the German manufacturing sector. With only a few expectations, MRPL-wage differences, which can be calculated from subtracting columns (1)-(4) from columns (5)-(8), are growing when moving up the wage, MRPL, size, and productivity distributions. The key mechanism reported in this study, that high wages are associated with higher labor market rents of firms which exerts a strong moderating effect of labor market power on firm pay differences is thus validated for almost all countries. Only in Switzerland, wages grow stronger than MRPL along the size distributions. Yet, even here, MRPL growth exceeds wage growth along the MRPL and size distributions.

As columns (9)-(16) show, labor (product) market power grows (slightly falls) along the wage, MRPL, and productivity distributions in most countries. This is consistent with evidence on Germany and shows that high wage and highly productive firms generate large labor market rents while being active on competitive product markets.

In sum, I therefore conclude that the inequality moderating effect of labor market power, particularly driven from high labor market power at high-paying "superstar" firms, is a wide-spread phenomenon across several European countries and sectors and not just a specificity of the German manufacturing sector.

TABLE 6

WAGES, MARGINAL REVENUE PRODUCTS OF LABOR, PRODUCTIVITY, AND PRODUCT AND LABOR MARKET POWER FOR FIRM VENTILES OF THE FIRM WAGE, SIZE, AND MRPL DISTRIBUTIONS

	Firm wages along wage, MRPL, size, and productivity distributions				MRPL along wage, MRPL, size, and productivity distributions				LMP along wage, MRPL, size, and productivity distributions				PMP along wage, MRPL, size, and productivity distributions			
	Wage distrib.	MRPL distrib.	Size distrib.	Prod. distrib.	Wage distrib.	MRPL distrib.	Size distrib.	Prod. distrib.	Wage distrib.	MRPL distrib.	Size distrib.	Prod. distrib.	Wage distrib.	MRPL distrib.	Size distrib.	Prod. distrib.
Country	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	3,622***	2,167***	838.2***	3,042***	4,153***	8,422***	652.8***	4,577***	0.042***	0.22***	-0.001**	0.069***	-0.016***	-0.0816***	0.001***	-0.011***
Italy	(89.31)	(88.46)	(27.59)	(64.94)	(94.28)	(518.3)	(22.19)	(134.7)	(0.00315)	(0.0129)	(0.0005)	(0.001)	(0.00252)	(0.00415)	(0.0002)	(0.00169)
	3,207***	1,714***	529.8***	2,756***	4,046***	8,656***	738.0***	4,376***	0.049***	0.26***	0.011***	0.075***	-0.02***	-0.132***	-0.002***	-0.012***
Spain	(107.2)	(43.93)	(25.96)	(54.02)	(143.4)	(619.3)	(40.02)	(212.7)	(0.00135)	(0.0163)	(0.001)	(0.003)	(0.001)	(0.0126)	(0.00042)	(0.0015)
	3,931***	1,653***	122.1	2,543***	4,256***	10,465***	570.3***	4,279***	0.024***	0.23***	-0.01***	0.055***	-0.012***	-0.105***	-0.0003	0.00217
Belgium	(138.9)	(68.26)	(87.43)	(60.52)	(134.3)	(538.8)	(34.98)	(129.8)	(0.00295)	(0.0103)	(0.00232)	(0.0022)	(0.00225)	(0.00919)	(0.00093)	(0.00160)
	2,604***	1,060***	43.80	2,089***	2,764***	7,213***	192.7***	3,306***	0.00521*	0.26***	-0.005*	0.055***	0.0039***	-0.0906***	-0.001	-0.00140
Slovenia	(95.50)	(49.05)	(56.74)	(63.97)	(115.7)	(372.8)	(19.34)	(92.84	(0.00311)	(0.0103)	(0.00236)	(0.0026)	(0.0014)	(0.00599)	(0.0008)	(0.00155)
	1,772***	1,011***	395.5***	1,745***	2,516***	4,762***	-116.0***	2,491***	-0.05***	0.24***	-0.03***	0.060***	0.0125***	-0.0588***	0.007***	0.012***
Poland	(87.42)	(41.18)	(21.90)	(48.93)	(101.9)	(264.9)	(27.57)	(91.32)	(0.005)	(0.009)	(0.001)	(0.001)	(0.0006)	(0.00315)	(0.0002)	(0.00054)
	1,863***	667.4***	-141.9**	1,329***	2,893***	9,320***	259.5***	4,317***	-0.0087	0.63***	-0.05***	0.184***	0.0137***	-0.222***	0.013***	0.0189***
Croatia	(72.58)	(35.22)	(68.12)	(39.20)	(119.7)	(584.9)	(14.61)	(136.8)	(0.00574)	(0.0327)	(0.00649)	(0.003)	(0.00235)	(0.0202)	(0.0021)	(0.00309)
	3,836***	2,844***	1,050***	2,064***	7,542***	13,509***	1,420***	2,076***	0.143***	0.39***	0.087***	0.031*	-0.196***	-0.458***	-0.015***	0.301***
Denmark	(49.27)	(95.47)	(46.52)	(197.70)	(147.50)	(768.60)	(102.60)	(551.20)	(0.0072)	(0.024)	(0.0032)	(0.0161)	(0.014)	(0.038)	(0.0028)	(0.0644)
	2,647***	1,155***	555.7***	1,982***	2,760***	7,104***	672.1***	2,882***	0.02***	0.22***	0.01***	0.046***	-0.004***	-0.0917***	-0.005***	0.000493
Finland	(62.42)	(43.08)	(25.38)	(38.99)	(70.10)	(334.5)	(54.46)	(77.42)	(0.00226)	(0.01)	(0.001)	(0.002)	(0.00144)	(0.00276)	(0.001)	(0.00174)
	3,159***	1,735***	317.4***	1,688***	8,434***	14,792***	2,074***	4,365***	0.154***	0.38***	0.053***	0.053***	-0.312***	-0.861***	-0.039***	0.0889***
Sweden	(54.24)	(76.88)	(23.40)	(92.11)	(208.0)	(544.9)	(131.0)	(464.3)	(0.008)	(0.0134)	(0.00435)	(0.0117)	(0.0491)	(0.142)	(0.004)	(0.0331)
	5,372***	2,669***	472.8***	4,404***	4,028***	8,814***	826.6***	3,585***	0.02***	0.14***	0.01***	0.022***	-0.018***	-0.203***	-0.012***	0.00870*
Switzerland	(208.3)	(82.56)	(62.70)	(124.2)	(147.5)	(570.1)	(95.53)	(182.1)	(0.00243)	(0.008)	(0.002)	(0.0028)	(0.00462)	(0.0166)	(0.00258)	(0.00477)

Notes: Table 6 reports results from estimating equation (13) for the wage, MRPL, size, and labor productivity distribution separately for each country of the CompNet data sample. The dependent variables in columns (1)-(4), columns (5)-(8), columns (9)-(12), columns (13)-(16) are respectively median values of firms' average wage, MRPL, labor market power, and product market power within year-country-distribution-decile bins of the respective distribution. The coefficients report the average change in the dependent variable when moving up the reported firm distribution by one decile. For Sweden, I excluded the top and bottom decile for all distributions due to extreme outlier values in average markups. All regressions include year fixed effects. Robust standard errors are reported in parentheses. Significance: *10 percent, **5 percent, ***1 percent. CompNet data.

6 Conclusion

This article sheds light on the role of labor market power in explaining increasing between-firm wage inequality using firm-level data for Germany's manufacturing sector from 1995 to 2016. I show that firms' labor market power had an important moderating effect on the documented rise in between-firm wage inequality. This holds at the aggregate manufacturing sector level, within regions, and within narrow industries. The mechanism behind this finding is that small, low-wage, low-MRPL firms possess no labor market power and pay wages equal to or above their MRPL, whereas large, high-wage, high-MRPL firms, possess high labor market power and pay wages far below their MRPL. These labor market power heterogeneities compress the firm wage distribution relative to a counterfactually competitive labor market and contribute to between-firm wage equality. Over past decades, this inequality moderating effect of labor market power became increasingly stronger.

Particularly in the largest, highest-paying, and highest-MRPL firms, which are also the most productive firms, MRPL-wage differences strongly widen over time. Despite wages grew within these top firms, the larger increase in their MRPL implies that these firms' (rising) labor market power exerts a strong moderating effect on (rising) between-firm wage inequality. This is because under competitive labor markets, wage gains would have been even larger in these top firms. While these "superstar firms" generate enormous rents from labor markets, they are active on competitive product markets. This highlights the relevance of labor markets rents for "superstar firms" and provides new insights on why such firms are particularly profitable and successful.

I show that my findings are not unique to the German manufacturing sector. Instead, the inequality-moderating effect of labor market power from high-wage, high-productivity firms paying wages far below competitive levels is a robust feature of several other European countries and occurs also outside of manufacturing.

My findings challenge the view that labor market power causes firm wage differences, which is a key feature of a large labor market literature and a main result of the rent-sharing literature (Card et al. (2018)). The main difference between my approach and the existing rent-sharing literature is that I allow for firm heterogeneities in labor market power (or rent-sharing parameters). Without such heterogeneities, there is a positive connection between labor market power and between-firm wage differences by construction. My findings therefore call for a serious reevaluation of this long-standing view. Overall, my results are supportive of factors other than labor market power causing firm wage differences, like differences in worker skills, production technologies, or firm-worker sorting effects.

Finally, my study informs recent debates on the effects of firm labor market power and the design of policies to regulate it. Policies addressing labor market power targeted at low-wage firms are unlikely to successfully reduce labor market power as most of it is concentrated in high-paying and highly productive firms. Firms that pay on average low wages are not necessarily monopsonists but may pay low wages because of low marginal revenue products. Binding minimum wages would make these firms unprofitable and force them to exit the market. The design of policies targeted at the regulation of labor markets must consider such characteristics of labor market power.

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Tables separately for reviewers

TABLE 1

DISPERSION IN WAGES, MARGINAL REVENUE PRODUCTS OF LABOR, AND LABOR MARKET POWER, BY TWO-DIGIT INDUSTRY

		Wages			Marginal revenue products of labor			Labor market power		
	Obs.	Median	Sd.	Percentile diff. (90-10)	Median	Sd.	Percentile diff. (90-10)	Median	Sd.	Percentile diff. (90-10)
Sector		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
15 Food products and beverages	29,455	23,003€	10,882€	27,634€	14,832€	10,999€	25,727€	0.66	0.28	0.67
17 Textiles	8,369	28,254€	8,721€	21,683€	30,288€	9,938€	25,729€	1.11	0.32	0.77
18 Apparel, dressing, and dyeing of fur	3,200	23,932€	8,096€	20,003€	17,129€	10,641€	19,102€	0.77	0.32	0.68
19 Leather and leather products	1,811	25,030€	7,326€	19,393€	20,943€	11,045€	24,511€	0.88	0.36	0.85
20 Wood and wood products	6,766	29,310€	7,923€	20,380€	22,637€	20,302€	48,932€	0.85	0.57	1.36
21 Pulp, paper, and paper products	6,693	34,710€	9,127€	23,669€	35,319€	22,475€	53,354€	1.08	0.48	1.20
22 Publishing and printing	5,928	34,172€	10,305€	26,758€	21,677€	15,966€	35,088€	0.69	0.40	0.91
24 Chemicals and chemical products	14,851	40,818€	12,468€	31,713€	45,185€	28,334€	68,519€	1.10	0.63	1.47
25 Rubber and plastic products	15,844	31,420€	8,772€	22,483€	24,506€	15,267€	32,786€	0.84	0.37	0.85
26 Other non-metallic mineral products	13,286	33,637€	9,177€	23,388€	34,948€	18,502€	47,909€	1.06	0.45	1.10
27 Basic metals	9,587	38,252€	9,196€	24,201€	48,759€	33,553€	78,561€	1.32	0.70	1.67
28 Fabricated metal products	32,795	32,964€	8,972€	22,538€	27,189€	15,756€	36,472€	0.88	0.39	0.95
29 Machinery and equipment	40,070	38,616€	10,146€	25,943€	38,130€	21,462€	49,170€	1.01	0.44	1.03
30 Electrical and optical equipment	1,980	37,885€	11,871€	29,462€	33,071€	37,302€	65,316€	0.92	0.84	1.52
31 Electrical machinery and apparatus	14,772	33,881€	10,542€	27,306€	29,822€	23,209€	50,996€	0.92	0.54	1.22
32 Radio, television, and communication	4,338	33,683€	12,233€	30,052€	38,495€	32,500€	63,553€	1.17	0.74	1.50
33 Medical and precision instruments	10,534	35,088€	12,449€	31,986€	33,975€	31,918€	71,396€	0.96	0.68	1.46
34 Motor vehicles and trailers	8,412	34,919€	10,561€	26,467€	38,065€	30,079€	52,497€	1.14	0.54	1.14
35 Transport equipment	2,549	31,510€	8,429€	21,591€	26,176€	9,476€	24,634€	0.81	0.35	0.88
36 Furniture manufacturing	11,742	29,395€	8,498€	21,825€	24,848€	13,918€	31,477€	0.91	0.39	0.91
Across all industries	242,982	33,211€	11,091€	28,284€	29,650€	23,301€	50,401€	0.93	0.51	1.13

Notes: Table 1 reports medians, standard deviations, and 90-10 percentile differences for wages, marginal revenue products of labor, and labor market power. Wages and marginal revenue products of labor are expressed in values of 1995. Germany’s manufacturing sector. Sample firms.

TABLE 2

SELECTED PERCENTILE DIFFERENCES FOR FIRM WAGES AND MARGINAL REVENUE PRODUCTS OF LABOR OVER TIME, ENTIRE MANUFACTURING SECTOR

Year	Percentile differences firm wages			Percentile differences firm MRPL			Diff. between column 4 and 1
	90-10	90-50	50-10	90-10	90-50	50-10	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1995	24,525€	12,041€	12,484€	43,502€	28,724€	14,778€	18,977€
2000	27,148€	13,492€	13,656€	46,775€	31,247€	15,528€	19,628€
2005	29,141€	14,766€	14,375€	52,861€	35,763€	17,098€	23,720€
2010	28,869€	15,641€	13,228€	53,292€	36,991€	16,302€	24,423€
2016	30,578€	16,687€	13,891€	51,321€	35,037€	16,284€	20,743€

Notes: Table 2 reports 90-10, 90-50, and 50-10 percentile differences of the firm distribution for wages and marginal revenue products of labor. Wages and marginal revenue products of labor are expressed in values of 1995. Germany’s manufacturing sector. Sample firms.

TABLE 3

SELECTED PERCENTILE DIFFERENCES FOR FIRM WAGES AND MARGINAL REVENUE PRODUCTS OF LABOR OVER TIME, WITHIN FOUR-DIGIT INDUSTRIES AND FEDERAL STATES.

Panel A: Within four-digit industries

Coefficient on year dummies	Percentile differences firm wages			Percentile differences firm MRPL			Diff. column 4 and 1
	90-10	90-50	50-10	90-10	90-50	50-10	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2000	795.1€ (339.2€)	662.8€ (259.2€)	132.4€ (245.6€)	2,660€ (925.0€)	2,506€ (802.9€)	154.0€ (409.9€)	1,864.9€
2005	2,674€ (336.3€)	1,937€ (260.3€)	737.1€ (259.0€)	5,730€ (911.8€)	4,167€ (841.2€)	1,562€ (365.9€)	3,056.0€
2010	2,481€ (342.7€)	2,600€ (283.1€)	-118.9€ (237.0€)	6,982€ (1,062€)	6,049€ (951.9€)	932.9€ (370.3€)	2,481.0€
2016	2,597€ (370.0€)	2,662€ (306.0€)	-65.32€ (257.4€)	5,688€ (1,113€)	5,181€ (1,048€)	506.8€ (373.5€)	3,091.0€

Panel B: Within federal states

Coefficient on year dummies	Percentile differences firm wages			Percentile differences firm MRPL			Diff. column 4 and 1
	90-10	90-50	50-10	90-10	90-50	50-10	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2000	3,811€ (804.1€)	2,700€ (703.8€)	1,111€ (294.5€)	3,292€ (1,342€)	2,565€ (1,354€)	727.9€ (507.7€)	-519.0€
2005	5,794€ (379.5€)	2,996€ (352.6€)	2,798€ (283.4€)	10,566€ (1,393€)	7,997€ (1,283€)	2,569€ (438.4€)	4,772.0€
2010	5,626€ (579.0€)	3,835€ (369.5€)	1,791€ (379.0€)	11,633€ (1,339€)	9,593€ (1,204€)	2,040€ (396.7€)	6,007.0€
2016	6,709€ (943.1€)	4,391€ (513.1€)	2,318€ (548.3€)	9,344€ (1,169€)	7,930€ (1,062€)	1,415€ (513.1€)	2,635.0€

Notes: Table 3 reports coefficients and standard errors from a regression of 90-10, 90-50, and 50-10 percentile differences on a full set of year dummies and either a full set of four-digit industry dummies (Panel A) or a full set of federal state dummies (Panel B). The coefficients report the average changes in percentile differences within four-digit industries (Panel A) or federal states (Panel B), relative to the base year 1995. Columns 1-3 show percentile differences for firm wages. Columns 4-6 show percentile differences for firms' marginal revenue products of labor. Standard errors are reported in parentheses and clustered at the four-digit industry (Panel A) or federal state (Panel B) level. Euro values of 1995. Germany's manufacturing sector. Sample firms.

TABLE 4

DISPERSION IN WAGES, MARGINAL REVENUE PRODUCTS OF LABOR, AND LABOR MARKET POWER, BY SECTOR

	Mean values for firm wage ventiles					Mean values for number of employees ventiles					Mean values for MRPL ventiles				
	Wage	MRPL	Labor prod.	PMP	LMP	Wage	MRPL	Labor prod.	PMP	LMP	Wage	MRPL	Labor prod.	PMP	LMP
Ventiles (P = percentile)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Firms ≤ 5P	13,487€	12,296€	9.78	1.02	0.92	29,051€	19,423€	10.36	1.13	.69	18,510€	7,973€	9.97	1.19	.49
Firms > 5P and ≤ 10P	17,899€	17,320€	10.02	1.04	0.97	28,957€	21,263€	10.37	1.13	.75	22,610€	11,957€	10.14	1.16	.59
Firms > 10P and ≤ 15P	20,768€	20,900€	10.18	1.05	1.01	29,139€	22,462€	10.37	1.12	.79	25,549€	14,734€	10.28	1.16	.63
Firms > 15P and ≤ 20P	22,950€	23,099€	10.27	1.06	1.01	29,593€	23,604€	10.40	1.11	.82	26,855€	16,902€	10.3	1.14	.69
Firms > 20P and ≤ 25P	24,841€	24,720€	10.34	1.07	1.00	30,019€	24,661€	10.41	1.11	.84	28,241€	18,876€	10.35	1.14	.73
Firms > 25P and ≤ 30P	26,535€	26,362€	10.39	1.08	.99	30,590€	25,876€	10.45	1.11	.86	29,212€	20,734€	10.40	1.13	.77
Firms > 30P and ≤ 35P	28,121€	27,751€	10.45	1.08	.99	30,679€	27,155€	10.45	1.10	.90	30,060€	22,574€	10.45	1.12	.81
Firms > 35P and ≤ 40P	29,625€	29,197€	10.49	1.09	.99	31,405€	28,497€	10.48	1.10	.92	31,063€	24,450€	10.47	1.11	.84
Firms > 40P and ≤ 45P	31,069€	30,278€	10.53	1.10	.98	31,580€	29,959€	10.50	1.09	.96	32,033€	26,421€	10.51	1.11	.88
Firms > 45P and ≤ 50P	32,476€	32,130€	10.55	1.10	.99	31,950€	31,058€	10.52	1.09	.98	32,890€	28,565€	10.53	1.09	.93
Firms > 50P and ≤ 55P	33,885€	33,607€	10.62	1.10	.99	32,551€	32,402€	10.54	1.09	1.00	33,815€	30,832€	10.58	1.09	.97
Firms > 55P and ≤ 60P	35,311€	35,707€	10.66	1.10	1.01	33,254€	34,488€	10.57	1.08	1.04	34,663€	33,285€	10.60	1.08	1.02
Firms > 60P and ≤ 65P	36,741€	37,226€	10.70	1.11	1.01	33,420€	35,818€	10.57	1.08	1.08	35,576€	35,977€	10.64	1.07	1.07
Firms > 65P and ≤ 70P	38,232€	39,221€	10.74	1.11	1.03	34,276€	38,138€	10.61	1.07	1.12	36,824€	39,020€	10.69	1.07	1.12
Firms > 70P and ≤ 75P	39,830€	41,727€	10.78	1.11	1.05	35,151€	41,061€	10.64	1.07	1.17	37,927€	42,572€	10.72	1.05	1.18
Firms > 75P and ≤ 80P	41,580€	44,544€	10.81	1.11	1.07	36,156€	43,745€	10.65	1.06	1.21	39,372€	46,748€	10.75	1.04	1.25
Firms > 80P and ≤ 85P	43,639€	48,726€	10.86	1.11	1.12	37,828€	47,354€	10.70	1.06	1.26	40,869€	52,008€	10.81	1.03	1.34
Firms > 85P and ≤ 90P	46,147€	52,944€	10.91	1.11	1.15	39,619€	51,719€	10.76	1.06	1.30	42,510€	59,315€	10.89	1.02	1.47
Firms > 90P and ≤ 95P	49,707€	59,281€	10.97	1.11	1.19	40,937€	57,374€	10.76	1.05	1.39	44,662€	70,791€	11.01	1.00	1.66
Firms > 95P	58,394€	69,974€	11.09	1.11	1.20	45,379€	72,207€	10.90	1.03	1.58	47,986€	103,307€	11.12	.97	2.23
Overall average	33,560€	35,348	10.55	1.09	1.03	33,560€	35348€	10.55	1.09	1.03	33,560€	35,348€	10.55	1.09	1.03
Total observations	242,982	242,982	222,215	242,982	242,982	242,982	242,982	222,215	242,982	242,982	242,982	242,982	222,215	242,982	242,982

Notes: Table 4 reports averages for wages, marginal revenue products of labor, labor productivity, firms' product market power, and firms' labor market power for each ventile the firm wage, size (employment), and MRPL distributions. Wages and marginal revenue products of labor are expressed in values of 1995. Germany's manufacturing sector. Sample firms.

TABLE 5

MRPL AND FIRM WAGE DISPERSION IN SEVERAL EUROPEAN COUNTRIES

Country	Years (1)	Average firm wage (2)	90-10 percentile differences, wage distribution (3)	90-10 percentile differences, MRPL distribution (4)	Time trend of differences between MRPL and wage dispersion (5)
Italy	2006-2019	30,676.12€	28,296.22€	64,539.35€	-1,320.67*** (225.01)
Spain	2008-2018	28,176.89€	26,296.81€	66,736.65€	-147.62 (264.10)
Belgium	2000-2018	39,470.57€	32,338.87€	82,421.75€	482.81*** (143.82)
Slovenia	2002-2019	25,414.64€	22,323.28€	53,789.52€	556.94*** (103.24)
Poland	2002-2019	16,750.54€	19,840.09€	36,673.02€	302.05*** (38.33)
Croatia	2002-2019	14,171.30€	15,681.26€	70,533.57€	-1,386.22*** (241.19)
Denmark	2004-2016	29,565.18€	33,534.12€	101,603.2€	-1,185.22 (874.48)
Finland	1999-2019	29,548.92€	23,098.78€	55,550.73€	-559.51*** (84.22)
Sweden	2003-2019	37,512.13€	32,146.18€	14,9761.3€	-1,222.56** (516.85)
Switzerland	2009-2018	53,517.75€	44,752.45€	66,230.91€	53.64 (272.01)

Notes: Table 5 shows MRPL and firm wage dispersion for several European countries. Column (1) reports the years of observation, column (2) reports the average firm wage and column (3) and (4) respectively show average 90-10 percentile differences for firms' wages and MRPL across all years (values of 2005, PPP deflated). Column (5) reports the coefficient from a regression of the difference in wage and MRPL dispersion (column (4) minus column (3) for every year) on a linear time trend. Robust standard errors for column (5) are reported in parentheses. Significance: *10 percent, **5 percent, ***1 percent. CompNet data.

TABLE 6

WAGES, MARGINAL REVENUE PRODUCTS OF LABOR, PRODUCTIVITY, AND PRODUCT AND LABOR MARKET POWER FOR FIRM VENTILES OF THE FIRM WAGE, SIZE, AND MRPL DISTRIBUTIONS

	Firm wages along wage, MRPL, size, and productivity distributions				MRPL along wage, MRPL, size, and productivity distributions			
	Wage distrib.	MRPL distrib.	Size distrib.	Prod. distrib.	Wage distrib.	MRPL distrib.	Size distrib.	Prod. distrib.
Country	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	3,622***	2,167***	838.2***	3,042***	4,153***	8,422***	652.8***	4,577***
Italy	(89.31)	(88.46)	(27.59)	(64.94)	(94.28)	(518.3)	(22.19)	(134.7)
	3,207***	1,714***	529.8***	2,756***	4,046***	8,656***	738.0***	4,376***
Spain	(107.2)	(43.93)	(25.96)	(54.02)	(143.4)	(619.3)	(40.02)	(212.7)
	3,931***	1,653***	122.1	2,543***	4,256***	10,465***	570.3***	4,279***
Belgium	(138.9)	(68.26)	(87.43)	(60.52)	(134.3)	(538.8)	(34.98)	(129.8)
	2,604***	1,060***	43.80	2,089***	2,764***	7,213***	192.7***	3,306***
Slovenia	(95.50)	(49.05)	(56.74)	(63.97)	(115.7)	(372.8)	(19.34)	(92.84
	1,772***	1,011***	395.5***	1,745***	2,516***	4,762***	-116.0***	2,491***
Poland	(87.42)	(41.18)	(21.90)	(48.93)	(101.9)	(264.9)	(27.57)	(91.32)
	1,863***	667.4***	-141.9**	1,329***	2,893***	9,320***	259.5***	4,317***
Croatia	(72.58)	(35.22)	(68.12)	(39.20)	(119.7)	(584.9)	(14.61)	(136.8)
	3,836***	2,844***	1,050***	2,064***	7,542***	13,509***	1,420***	2,076***
Denmark	(49.27)	(95.47)	(46.52)	(197.70)	(147.50)	(768.60)	(102.60)	(551.20)
	2,647***	1,155***	555.7***	1,982***	2,760***	7,104***	672.1***	2,882***
Finland	(62.42)	(43.08)	(25.38)	(38.99)	(70.10)	(334.5)	(54.46)	(77.42)
	3,159***	1,735***	317.4***	1,688***	8,434***	14,792***	2,074***	4,365***
Sweden	(54.24)	(76.88)	(23.40)	(92.11)	(208.0)	(544.9)	(131.0)	(464.3)
	5,372***	2,669***	472.8***	4,404***	4,028***	8,814***	826.6***	3,585***
Switzerland	(208.3)	(82.56)	(62.70)	(124.2)	(147.5)	(570.1)	(95.53)	(182.1)

	LMP along wage, MRPL, size, and productivity distributions				PMP along wage, MRPL, size, and productivity distributions			
	Wage distrib.	MRPL distrib.	Size distrib.	Prod. distrib.	Wage distrib.	MRPL distrib.	Size distrib.	Prod. distrib.
Country	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	0.042***	0.22***	-0.001**	0.069***	-0.016***	-0.0816***	0.001***	-0.011***
Italy	(0.00315)	(0.0129)	(0.0005)	(0.001)	(0.00252)	(0.00415)	(0.0002)	(0.00169)
	0.049***	0.26***	0.011***	0.075***	-0.02***	-0.132***	-0.002***	-0.012***
Spain	(0.00135)	(0.0163)	(0.001)	(0.003)	(0.001)	(0.0126)	(0.00042)	(0.0015)
	0.024***	0.23***	-0.01***	0.055***	-0.012***	-0.105***	-0.0003	0.00217
Belgium	(0.00295)	(0.0103)	(0.00232)	(0.0022)	(0.00225)	(0.00919)	(0.00093)	(0.00160)
	0.00521*	0.26***	-0.005*	0.055***	0.0039***	-0.0906***	-0.001	-0.00140
Slovenia	(0.00311)	(0.0103)	(0.00236)	(0.0026)	(0.0014)	(0.00599)	(0.0008)	(0.00155)
	-0.05***	0.24***	-0.03***	0.060***	0.0125***	-0.0588***	0.007***	0.012***
Poland	(0.005)	(0.009)	(0.001)	(0.001)	(0.0006)	(0.00315)	(0.0002)	(0.00054)
	-0.0087	0.63***	-0.05***	0.184***	0.0137***	-0.222***	0.013***	0.0189***
Croatia	(0.00574)	(0.0327)	(0.00649)	(0.003)	(0.00235)	(0.0202)	(0.0021)	(0.00309)
	0.143***	0.39***	0.087***	0.031*	-0.196***	-0.458***	-0.015***	0.301***
Denmark	(0.0072)	(0.024)	(0.0032)	(0.0161)	(0.014)	(0.038)	(0.0028)	(0.0644)
	0.02***	0.22***	0.01***	0.046***	-0.004***	-0.0917***	-0.005***	0.000493
Finland	(0.00226)	(0.01)	(0.001)	(0.002)	(0.00144)	(0.00276)	(0.001)	(0.00174)
	0.154***	0.38***	0.053***	0.053***	-0.312***	-0.861***	-0.039***	0.0889***
Sweden	(0.008)	(0.0134)	(0.00435)	(0.0117)	(0.0491)	(0.142)	(0.004)	(0.0331)
	0.02***	0.14***	0.01***	0.022***	-0.018***	-0.203***	-0.012***	0.00870*
Switzerland	(0.00243)	(0.008)	(0.002)	(0.0028)	(0.00462)	(0.0166)	(0.00258)	(0.00477)

Notes: Table 6 reports results from estimating equation (13) for the wage, MRPL, size, and labor productivity distribution separately for each country of the CompNet data sample. The dependent variables in columns (1)-(4), columns (5)-(8), columns (9)-(12), columns (13)-(16) are respectively median values of firms' average wage, MRPL, labor market power, and product market power within year-country-distribution-decile bins of the respective distribution. The coefficients report the average change in the dependent variable when moving up the reported firm distribution by one decile. For Sweden, I excluded the top and bottom decile for all distributions due to extreme outlier values in average markups. All regressions include year fixed effects. Robust standard errors are reported in parentheses. Significance: *10 percent, **5 percent, ***1 percent. CompNet data.

Figures separately in higher quality - for reviewers and editing

DISTRIBUTION OF MARGINAL REVENUE PRODUCTS OF LABOR AND WAGES ACROSS FIRMS

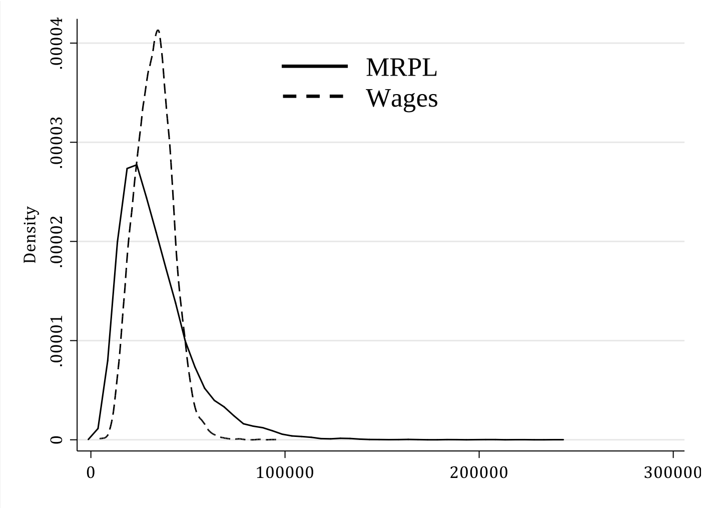

FIGURE 1 – Distribution of marginal revenue products of labor and average wages across firms in 1995. Results for other years and all years pooled look similar. Expressed in values of 1995. Germany's manufacturing sector. Sample firms.

BETWEEN-FIRM WAGE AND MRPL DISPERSION, OVER TIME

Panel A: Firm wage and MRPL dispersion

Panel B: Differences between firm wage and MRPL dispersion

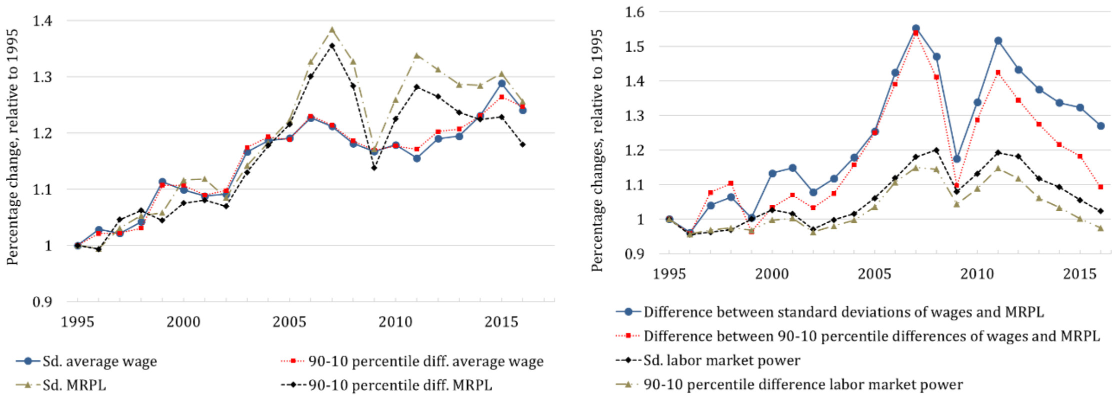

FIGURE 2 – Panel A: Standard deviations and 90-10 percentile differences for firms' wages and marginal revenue products of labor. Panel B: Differences between standard deviations and 90-10 percentile differences for firms' wages and marginal revenue products of labor together with the standard deviation and 90-10 percentile difference of labor market power. Values are normalized to unity in 1995. Germany's manufacturing sector. Sample firms.

FIRM WAGES AND MRPL OVER TIME FOR TOP AND BOTTOM VENTILE FIRMS

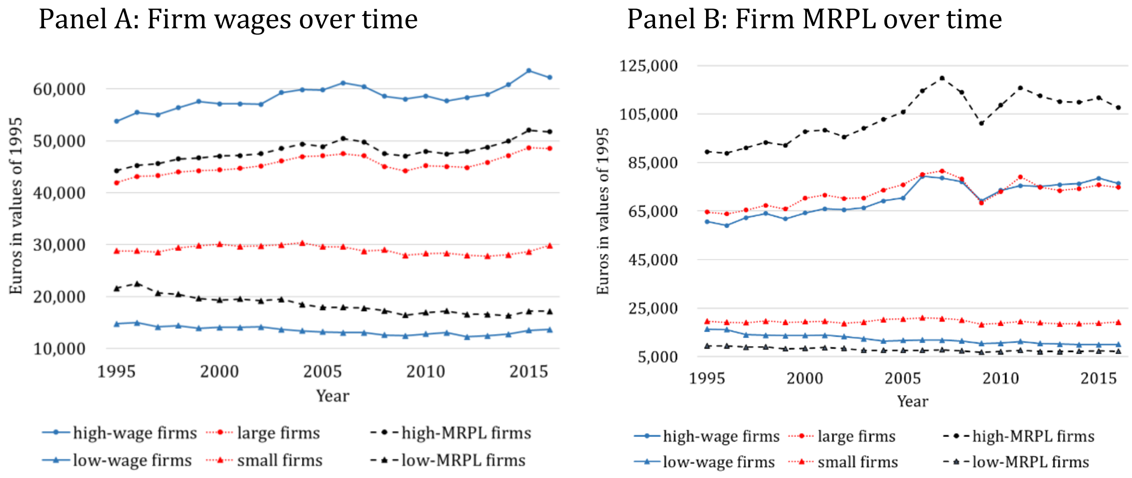

FIGURE 3 – Average firm wages and MRPL over time for the top and bottom ventiles of the firm wage, size, and MRPL distributions. Germany's manufacturing sector. Sample firms.

LABOR MARKET POWER OVER TIME FOR TOP AND BOTTOM VENTILE FIRMS

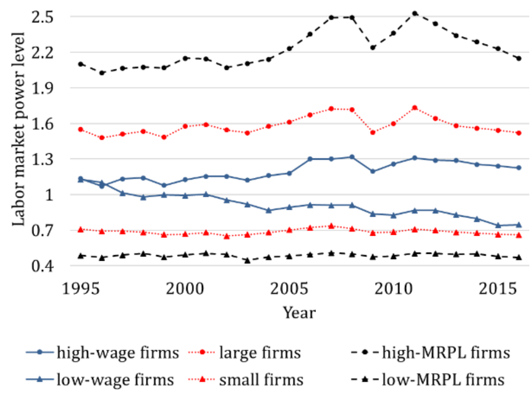

FIGURE 4 – Average labor market power over time for the top and bottom ventiles of the firm wage, size, and MRPL distributions. Germany's manufacturing sector. Sample firms.

Online Appendix – not for publication

Appendix A.1: Details on the German manufacturing sector data and summary statistics

Data access

The data can be accessed at the "Research Data Centres" of the Federal Statistical Office of Germany and the Statistical Offices of the German Länder. Data request can be made at: https://www.forschungsdatenzentrum.de/en/request.

The statistics that I used are: "AFiD-Modul Produkte", "AFiD-Panel Industriebetriebe", "AFiD-Panel Industrieunternehmen", "Investitionserhebung im Bereich Verarbeitendes Gewerbe, Bergbau und Gewinnung von Steinen und Erden", "Panel der Kostenstrukturerhebung im Bereich Verarbeitendes Gewerbe, Bergbau und Gewinnung von Steinen und Erden". The data are combined by the statistical offices and provided as a merged dataset.

Variable definitions

The following list presents an overview on the variable definitions of all variables used in this article. This includes variables used in other sections of the online Appendix.

- L_{it}: Labor in headcounts.
- w_{it}: Firm wage (firm average), defined as gross salary + "other social expenses" (latter includes expenditures for company outings, advanced training, and similar costs) divided by the number of employees.
- K_{it}: Capital derived by a perpetual inventory method (see online Appendix D), where investment captures firms' total investment in buildings, equipment, machines, and

other investment goods. Nominal values are deflated by a two-digit industry-level deflator supplied by the statistical office of Germany.

- 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.
- $z_{it}M_{it}$: Nominal values of total intermediate input expenditures.
- $P_{it}Q_{it}$: Nominal output / 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 π_{it}, see the definition of π_{it} below).[29]
- π_{it}: Firm-specific Törnqvist price index, derived as in Eslava, Haltiwanger, Kugler, & Kugler (2004). See the online Appendix C for its construction.
- p_{igt}: Price of a product g.
- $share_{igt}$: Revenue share of a product g 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. 90% of firms in my sample are single-plant firms.

[29] I observe quantities for the individual products of firms. Within multi-product firms, one cannot aggregate product quantities in a meaningful way. The measurement unit for each product is, however, designated by the statistical office. Hence, within products, aggregation of quantities is possible.

- 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} $(or\ in\ logs, e_{it})$: 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 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.

Summary statistics, German manufacturing sector data

TABLE A.1

SUMMARY STATISTICS FOR SAMPLE FIRMS

Variable	Mean (1)	Sd (2)	P25 (3)	Median (4)	P75 (5)	Observations (6)
Average real wage	33,560	11,091	25,666	33,211	40,646	242,982
Labor market power parameter	1.03	0.51	.069	0.93	1.25	242,982
MRPL	35,348	23,301	19,787	29,650	44,440	242,982
Product market power parameter	1.09	0.18	0.97	1.05	1.17	242,982
Number of employees	303.74	2,220.89	47	94	223	242,982
Deflated capital stock in thousands	39,900	408,000	2,384	6,673	21,100	242,982
Deflated intermediate input expenditures in thousands	49,200	743,000	2,649	7,047	22,400	242,982
Deflated capital per employee in thousands	95.97	96.04	38.03	68.54	119.88	242,982
Value-added over revenue	0.40	0.13	0.30	0.40	0.49	242,982
Value-added labor share	0.78	0.26	0.63	0.76	0.88	242,982
Nominal revenue in thousands	74,200	1,000,000	5,097	12,400	37,100	242,982
Log of real value-added per employee	10.55	0.87	10.12	10.61	11.06	222,215
Number of products	3.60	6.72	1	2	4	242,982
Export status dummy	0.78	0.42	1	1	1	242,982
Revenue weighted product market shares (euro-based, in percent)	10.79	17.65	0.77	3.23	12.28	242,982
Average real wage	33,560	11,091	25,666	33,211	40,646	242,982

Notes: Table A.1 reports sample summary statistics. Columns 1, 2, 3, 4, 5, and 6 respectively report the mean, standard deviation, 25th percentile, median, 75th percentile, and the number of observations used to produce summary statistics for the respective variable.

Deriving a time consistent industry classification

During my 22 years of data, the NACE classification of industry sectors (and thus firms into industries) changed twice. Once in 2002 and once in 2008. Because my estimation of labor market power relies on having a time-consistent industry classification at the firm level (as I allow for sector-specific production functions and as I use sector-specific deflators) it is crucial for me to recover a time-consistent NACE industry classification. Recovering such a time-consistent industry classification from official concordance tables is, however, problematic as they contain many ambiguous sector reclassifications.

To address this issue, I follow the procedure described in Mertens (2020a) and use information on firms' product mix to classify firms into NACE rev 1.1 sectors based on their main production activities. This procedure exploits that the first four digits of the ten-digit GP product classification reported in the German data are identical to the NACE sector classification (i.e. they indicate the industry of the product). Obviously, applying this method demands a consistent reclassification of all products into the GP2002 scheme (which corresponds to the NACE rev 1.1 scheme). Reclassifying products is, however, due to the granularity of the ten-digit classification, less ambiguous than reclassifying industries. In the few ambiguous cases, I can follow the firms' product mix over the reclassification periods and unambiguously reclassify most products (i.e. I observe what firms produce before and after reclassification years). Having constructed a time-consistent product-industry classification according to the GP2002 scheme, I attribute every firm to the NACE rev 1.1 industry in which it generates most of its revenue.[30] When comparing my classification with the one of the statistical offices for the years 2002-2008 (years in which industries are already reported in NACE rev 1.1), I find that my two-digit and four-digit classification of firms into industries matches the classification of the statistical offices in 95% and 86% of all cases, respectively.

Table A.2 provides a few examples on the product classifications within the product-level data used to calculate firm-specific price indices as described in online Appendix D. Table A.2 is taken from Mertens & Müller (2020).

[30] The statistical offices of Germany use a similar approach to classify firms into industries based on their revenue, employment, and value-added.

TABLE A.2

EXAMPLES OF INDUSTRY AND PRODUCT CLASSIFICATIONS

NACE rev. 1.1	Product code	Description
18		Manufacture of wearing apparel; dressing and dyeing of fur
1821		Manufacture of workwear
		Products
	182112410(0)	Long trousers for men, cotton (not contracted)
	182112510(0)	Overalls for men, cotton (not contracted)
	182112510(2)	Overalls for men, cotton (contracted production)
	182121350(2)	Coats for women, chemical fiber (contracted production)
27		Manufacture of basic metals
2743		Lead, zinc, and tin production
		Products
	274312300(0)	Zinc, unwrought, refined (not contracted)
	274311300(0)	Lead, unwrought, refined (not contracted)
	274311500(0)	Lead, unwrought, with antimony (not contracted)
	274328300(0)	Tin sheets and tapes, thicker than 0.2mm (not contracted)
	274328600(0)	Tin sheets and tapes, not thicker than 0.2mm (not contracted)

Notes: Table A.2 presents examples of the products available in our data. The reported GP2002 product codes define 6,500 distinct products at the nine-digit level from which we find 5,927 in our database and 4,194 in our final sample of firms. The last number of each product code (10^{th} position) indicates whether the product was manufactured as contracted work (2). Source: Mertens & Müller (2020).

Appendix A.2: The CompNet data

The CompNet data – collection and vintages

The CompNet data is collected by running harmonized data collection protocols over administrative firm-level data located in several national statistical institutes and central banks. These firm-level databases are arguably the best (in terms of coverage, quality, representativeness) available firm-level data sources for the respective countries included in CompNet. The data collection protocols calculate harmonized performance measures and other variables at the firm-level and aggregate these results to the two-digit-industry-, NUTS2-, one-digit-sector-, and country-level. A key feature of these aggregate statistics is that they also contain detailed information on the distribution (standard deviations, selected percentiles) of variables, allowing researchers to understand firm heterogeneity within the aggregation levels. After having executed the data collection protocols, data providers (statistical institutes and central banks) send back the aggregated results to the Scientific Staff of CompNet which combines the results into a final database. More details on this procedure can be found on: https://www.comp-net.org/data/7th-vintage/.

An important feature of the CompNet data is that it provides population weighted and non-population weighted versions of the data.[31] I focus on the former, but replications of my results using the non-weighted version did not change any results.

The data collection is done every 12-16 months. The information gathered varies between each data collection round, while there is a certain set of key variables included in

[31] The weights are based on the number of firms within a two-digit-industry-size-class-cell as reported on Eurostat. An advantage of the weighted data is that it is unaffected by differences in the number of firms underlying different variables. For instance, in the firm data underlying the CompNet data, wage information is more often available then data on firms' MRPL because the latter demands an estimation of the production function. The CompNet data reports the number of firms underlying each statistic and, despite differences, underlying firm numbers are very similar for wages and MRPL (see Table A.3).

every data collection. The results from the data collection are published as so called "CompNet vintages". The most recent publicly available data vintage is the 7th vintage. The data I use comes from the 8th vintage of the CompNet data, which I access via an early-access account. I do so, because key information on the marginal revenue product of labor (MRPL) is not included in the 7th vintage. Due to using the early-access version, my data does not contain all countries eventually being included in the publicly available 8th vintage data that is planned to be published in autumn 2021 (also Germany is not included in my data).[32] Details on the most recent and older vintages can be found on the CompNet webpage: https://www.comp-net.org/data/7th-vintage/. For a detailed treatment of the data, I refer to the most recent User-Guide version, which is constantly updated and can be accessed via the same weblink above.

Coverage and scope

As in previous vintages, the early-access data of the 8th vintage features information on almost all economic sectors. The data excludes agriculture and financial services as well as firms active in mining and quarrying. Moreover, the data contains only a restricted number of public service sectors. Overall, the data covers firms from nine broader sector categories:

- Manufacturing
- Construction
- Wholesale and retail trade
- Transportation and storage
- Accommodation and food service activities
- Information and Communication
- Real estate activities

[32] See Table A.3 for an overview on the country coverage of my data.

- Professional, scientific, and technical activities
- Administrative and support service

Notably, not every country provides information on all sectors. Similarly, the time-coverage for each country varies. Table A.3 summarizes the year and sector coverage of the data I use.

TABLE A.3

COMPNET DATA,
COVERAGE (FIRMS WITH AT LEAST 20 EMPLOYEES)

Country	Years (1)	Excluded sectors (2)	Average sample number of firms with information on wages (MRPL) (3)	Average population number of firms (4)
Italy	2006-2019	Real estate activities (for MRPL only)	48,096.69 (43,792.85)	73,136
Spain	2008-2018	None	37,199.45 (32,501.55)	61,046.18
Belgium	2000-2018	None	9,662.90 (4,467.42)	15,622.32
Slovenia	2002-2019	None	2,572.28 (2,132.44)	3,391.72
Poland	2002-2019	None	24,156.78 (22,756.72)	40,084.83
Croatia	2002-2019	None	4,563.94 (3,803.78)	6,266.17
Denmark	2004-2016	Real estate activities and ICT (for MRPL only)	9,833.31 (5,511.77)	12,342.38
Finland	1999-2019	Real estate activities	6,958.57 (5,536.14)	8,611.91
Sweden	2003-2019	None	12,544.06 (8,278.53)	17,065.18
Switzerland	2009-2018	None	6,387.70) (5,351.90)	19,809

Notes: Table A.3 reports basic statistics on the coverage of the CompNet data. Column (1) reports the years of coverage, column (2) lists the one-digit sectors excluded from the underlying firm-level dataset, column (3) shows the number of firms with wage and MRPL information in the underlying firm-level data (firm numbers for MRPL observations are reported in brackets), and column (4) reports the average population number of firms as reported on Eurostat. All statistics refer to firms with at least 20 employees.

Variables and statistics used from the CompNet data

The variables I use from the CompNet data are deflated average firm wages, firm labor market power, firm product market power, firm MRPL, firm size (number of employees), and the log of firm-level labor productivity (value-added divided by employees).

From the various data files in the CompNet data, I use the unconditional country- and one-digit sector-level data containing percentile values and standard deviations for all my variables of interest for every country and year. Additionally, I use the so called “joint distributions” that provide percentiles of my variables of interest by deciles of other variables.

Notably, as opposed to the sophisticated production function estimation of the main text, the market power measures as well as the MRPL I use from the CompNet data are based on a simple Cobb-Douglas production function estimated by OLS and which do not account for firm-specific price variation. The CompNet data also provides these variables based on a translog production function estimated by following the control function approach of Ackerberg, Caves, Frazer (2015), but due to this being the much more demanding specification in terms of data, the “joint distributions” only contain market power and MRPL estimates for the basic Cobb-Douglas specification estimated by OLS.[33]

I nevertheless checked my results on the distribution of firms’ MRPL being much more dispersed than the distribution of firm wages using the more sophisticated versions of the MRPL in the unconditional country- and one-digit-sector-level files and found that they are highly robust across the various production function specifications.

For more details on the CompNet data and its variables, I refer to CompNet’s User-Guide (CompNet 2020).[34]

[33] A general issue of the CompNet data is that is follow a “smallest common denominator” procedure due to achieving comparable results across countries, i.e. the production function estimation routines must work for all countries equally well. This and the short time span of the CompNet data are the reasons why my main analysis focuses on the German manufacturing sector data.

[34] Conceptionally the 7th and 8th vintage data are very similar, with the latter just containing improved data collection protocols, additional variables, and a more sophisticated statistical weighting procedure.

Data access

Researchers can request data access to the CompNet data via:
https://www.iwh-halle.de/en/research/data-and-analysis/research-data-centre/compnet-database/request-form/

Appendix B: Numerical example on how labor market power offsets existing firm pay differences

To illustrate that even small differences in labor market power can have large impacts on firm wage differences, let us use a simple example from the rent-sharing literature: The rent-sharing literature typically uses a rent-sharing/bargaining model to express wages (w_{it}) as a function of workers outside options ($\overline{w}_{it}$), profits per employees (or quasi-rents per employees), $\frac{\pi_{it}}{L_{it}}$, and a rent-sharing parameter (χ_{it}):

(B.1)
$$w_{it} = \overline{w}_{it} + \chi_{it}\frac{\pi_{it}}{L_{it}}.$$

Note that (B.1) is similar to equation (5) of the main text. From that, existing work motivates the estimation of rent-sharing parameters (χ_{it}) from regressing wages on value-added based labor productivity (Card et al. (2018)), which comes from multiplying $\frac{\pi_{it}}{L_{it}}$ with the value-added over profits (or quasi-rents) ratio. Using the resulting elasticity of wages to changes in labor productivity, existing work argues that productivity dispersion can cause significant wage dispersion through rent-sharing processes. For instance, using a rent-sharing elasticity of 0.08, Card et al. (2018) argue that a productivity spread between the 90th and 10th percentile of the (log) labor productivity distribution of 1.6, as reported in their data, implies a Lester range of wage variability between firms at the 90th and 10th percentile of $1.6 * 0.08 \approx 13$ log points.

Let us assume that the 10th and 90th percentile have values of 10 and 11.6, which are realistic values (see Table A.1). If the rent-sharing elasticity between these firms just differs by a factor of (10/11.6), rent sharing will create no wage variability at all: $10 * 0.08 = 11.6 * 0.08\ (10/11.6)$. Hence, if firms at the 10th percentile have a rent-sharing elasticity of 0.08, firms at the 90th percentile would just need to have a rent-sharing elasticity of 0.069 to eliminate the entire transmission from productivity dispersion to wage dispersion. If high-productivity firms have an even lower rent-sharing elasticity, the part of wages due to rent-sharing will even be lower in high-productivity firms. This would reduce any *existing* wage differences between high and low-productivity firms, as long as high-productivity firms still pay higher wages than low-productivity firms and thus contribute to between-firm wage equality. Given that Card et al. (2018) document large differences in average rent-sharing elasticities that have been reported in the literature across different countries and dataset (varying between 0.03 and 0.29), the above back-of-the-envelope calculations show that reasonably small differences in rent-sharing elasticities can create a between-firm-wage-inequality-moderating effect of labor market power, as long as there are other sources of firm wage differences that can be compensated by such labor market power differences (e.g. due to differences in workforce compositions between firms).

This argument can readily be extended to differences in labor supply elasticities as estimated in the literature on monopsonistic firm labor market power using a standard monopsonistic labor market model.

Appendix C: Estimating the production function

The following approach is closely in line with Mertens (2020a, 2020b) and follows the established work of Olley & Pakes (1996), Wooldridge (2009), and De Loecker et al. (2016). The general form of the translog production I apply writes:

(C.1) $$q_{it} = \boldsymbol{\phi}'_{it}\boldsymbol{\beta} + \omega_{it} + \varepsilon_{it}.$$

Lower case letters denote logs and $\boldsymbol{\phi}'_{it}$ captures the production inputs K_{it}, L_{it}, and M_{it} and its interactions.[35] ε_{it} is an i.i.d. error term and ω_{it} denotes Hicks-neutral productivity and follows a Markov process. Whereas ω_{it} is unobserved to the econometrician, firms know ω_{it} before making their input decisions for flexible inputs (i.e. intermediates in my case). As noted in the main text, I assume that only firms' input decision for intermediates depends on productivity shocks. Labor and capital do not respond to contemporary productivity shocks and are thus quasi-fixed inputs.

As mentioned in the main text, there are three issues preventing me from directly estimating the production function (C.1) with OLS:

i.) Although I observe product quantities, I cannot aggregate quantities across the various products of multi-product firms. Yet, I need to estimate a quantity-based production model to recover the relevant output elasticities. Relying on the standard practice to apply sector-specific output deflators does not solve this issue if output prices vary within industries.

[35] The production function is specified as: $q_{it} = \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} + \beta_{ll} l_{it}^2 + \beta_{mm} m_{it}^2 + \beta_{kk} k_{it}^2 + \beta_{lk} l_{it} k_{it} + \beta_{lm} l_{it} m_{it} + \beta_{km} k_{it} m_{it} + \beta_{lkm} l_{it} k_{it} m_{it} + \omega_{it} + \varepsilon_{it}$, where $\frac{\partial q_{it}}{\partial l_{it}} = \beta_l + 2\beta_{ll} l_{it} + \beta_{lm} m_{it} + \beta_{lk} k_{it} + \beta_{lkm} k_{it} m_{it}$ is the output elasticity of labor.

ii.) I do not observe firm-specific input prices for capital and intermediate inputs (I observe only output prices). If input prices are correlated with input decisions and output levels, I face an endogeneity issue.

iii.) The facts that productivity is unobserved and that firms' intermediate input decisions depend on productivity shocks create another endogeneity problem.

Below, I show how I address these problems and how this leads to equation (12) of the main text.

Solving issue 1: Deriving a firm-specific price index for firms' output

As it is impossible to aggregate output quantities across the different products of a firm, I construct a firm-specific price index from observed output price information following Eslava, Haltiwanger, Kugler, & Kugler (2004). I use this price index to purged observed firm revenue (for single- and multi-product firms) from price variation by deflating firm revenues with this price index.[36] Specifically, I construct firm-specific Törnqvist price indices for each firm's composite revenue from its various products:

(C.2) $$\pi_{it} = \prod_{g=1}^{n} \left(\frac{p_{igt}}{p_{igt-1}}\right)^{\frac{1}{2}(share_{igt}+share_{igt-1})} \pi_{it-1}.$$

π_{it} denotes the price index, p_{igt} is the price of good g, and $share_{igt}$ is the share of this good in total product market sales of firm i in period t. Hence, the growth of the index value is the product of the individual products' price growths, each weighted with the average sales share of that product over the current and the last year. I define the first year available in the data as the base year, i.e. $\pi_{t=1995} = 100$. For firms entering after 1995, I follow Eslava et al. (2004) in using an industry average of my firm price indices as a starting value.

[36] See also Smeets & Warzynski (2013) for an application of this approach.

Similarly, I follow Eslava et al. (2004) and impute missing product price growth information in other cases with an average of product price changes within the same industry.[37]

After deflating firm revenue with this price index, I end up with a quasi-quantity measure of output, for which, with slightly abusing notation, I keep using q_{it}.

Solving issue 2: Controlling for unobserved input price variation

To control for unobserved input price variation across firms, I follow De Loecker, Goldberg, Khandelwal, Pavcnik (2016) and define a price-control function from firm-product-level output price information that I add to the production function (C.1):

$$q_{it} = \widetilde{\boldsymbol{\phi}}_{it}'\boldsymbol{\beta} + B_{it}\big((\pi_{it}, ms_{it}, G_{it}, D_{it}) \times \boldsymbol{\phi}_{it}^{c}\big) \; + \; \omega_{it} + \varepsilon_{it}. \tag{C.3}$$

Comments on the notation are in order. $B_{it}(.) = B_{it}\big((\pi_{it}, ms_{it}, G_{it}, D_{it}) \times \boldsymbol{\phi}_{it}^{c}\big)$ is a price control function consisting of the firm-specific output price index (π_{it}), a weighted average of firms' product market shares in terms of revenues (ms_{it}), a headquarter location dummy (G_{it}) and a four-digit industry dummy (D_{it}). $\boldsymbol{\phi}_{it}^{c} = \{1; \widetilde{\boldsymbol{\phi}}_{it}\}$, where $\widetilde{\boldsymbol{\phi}}_{it}$ includes the same input terms as $\boldsymbol{\phi}_{it}$, either in monetary terms and deflated by an industry-level deflator (capital and intermediates) or already reported in quantities (i.e. labor). The tilde indicates that some variables in $\widetilde{\boldsymbol{\phi}}_{it}$ are not expressed in true quantities. The constant entering $\boldsymbol{\phi}_{it}^{c}$ highlights that elements of $B(.)$ enter the price control function linearly and interacted with $\widetilde{\boldsymbol{\phi}}_{it}$ (a consequence of the translog production function).

The idea behind the price-control function $B(.)$ is that output prices, product market shares, firm location, and firms' industry affiliation are informative about input prices of firms. Particularly, I assume that product prices and market shares contain information about product quality and that producing high-quality products demands expensive high-quality

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

inputs. As discussed in De Loecker et al. (2016), this motivates to add 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 form input quality differences across firms. Additionally, I include location and four-digit industry dummies into $B(.)$ to absorb remaining differences in local and four-digit industry-specific input prices. Conditional on elements in $B(.)$, I assume that there are no remaining input price differences across firms.[38] Although being restrictive, this assumption is more general than the ones employed in most other studies that estimate production functions without having access to firm-specific price data and which implicitly assume that firms face identical input and output prices within industries.

A notable difference between the original approach of De Loecker et al. (2016) and the one I apply is that De Loecker et al. (2016) estimate product-level production functions, whereas I transfer their framework to the firm-level. To do so, I use firm-product-specific sales shares in firms' total product market sales to aggregate firm-product-level information to the firm-level. By doing so, I assume that i) such firm aggregates of product quality increase in firm aggregates of product prices and input quality, ii) firm-level input costs for inputs entering as deflated expenditures are increasing in firm-level input quality, and iii) product price elasticities are equal across the various products of a firm. These assumptions, or even stricter versions of them, are always implicitly invoked when estimating firm- instead of product-level production functions.

Finally, note that even if some of the above assumptions do not hold, including the price control function is still preferable to omitting it. This is because the price control function can still absorb some of the unobserved price variation and does not demand that input prices

[38] I thus assume that input prices of intermediates and capital do not depend on input quantities, as these inputs enter the production function as deflated input expenditures.

vary between firms with respect to all elements of $B_{it}(.)$. 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 existence and degree of input price variation.

Solving issue 3: Controlling for unobserved productivity

To address the dependence of firms' flexible input decision on unobserved productivity, I employ a control function approach in the spirit of Olley & Pakes (1996). I base my control function on firms' consumption of energy and raw materials, which I denote both with e_{it} and which are components of total intermediate inputs. Inverting the demand function for e_{it} gives an expression for productivity:

(C.4) $$\omega_{it} \equiv g_{it}(.) = g_{it}(e_{it}, k_{it}, l_{it}, \mathbf{\Gamma}_{it}),$$

where $\mathbf{\Gamma}_{it}$ 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 broad set of variables affecting productivity and demand for e_{it}. In my specification, I include dummy variables for export (EX_{it}) activities, the log of the number of products a firm produces ($NumP_{it}$) and the average wage it pays (w_{it}) into $\mathbf{\Gamma}_{it}$. The latter absorbs unobserved quality and price differences that shift demand for e_{it}, which accounts for the criticism of Gandhi, Navarro, & Rivers (2020) (see also De Loecker & Scott (2016)).

Recap that productivity follows a first order Markov process. I allow that firms can shift this Markov process, giving rise to the following law of motion for productivity: $\omega_{it} = h_{it}(\omega_{it-1}, \boldsymbol{T}_{it-1}) + \xi_{it} = h_{it}(.) + \xi_{it}$, where ξ_{it} denotes the innovation in productivity and $\boldsymbol{T}_{it} = (EX_{it}, NumP_{it})$ reflects that I allow for learning effects from export market participation and (dis)economies of scope through adding and dropping products to influence firm productivity.[39] Plugging (C.4) and the law of motion for productivity into (C.3) gives:

(C.5)
$$q_{it} = \tilde{\boldsymbol{\phi}}'_{it}\boldsymbol{\beta} + B_{it}(.) + h_{it}(.) + \varepsilon_{it} + \xi_{it},$$

which constitutes the basis of my estimation and is identical to equation (12) of the main text.

Identifying moments

I estimate equation (12) separately by two-digit NACE rev. 1.1 industries using a one-step estimator as in Wooldridge (2009).[40] This 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}. Similarly, I use lagged values of terms including firms' market share and output price index as instruments for their contemporary values as I consider these to be flexible variables.[41] I define identifying moments jointly on ε_{it} and ξ_{it}:

(C.6)
$$E\big((\varepsilon_{it} + \xi_{it})\boldsymbol{\Upsilon}_{it}\big) = 0,$$

where $\boldsymbol{\Upsilon}_{it}$ includes lagged interactions of intermediate inputs with labor and capital, contemporary interactions of labor and capital, contemporary location and industry

[39] $\boldsymbol{T}_{it}$ and $\boldsymbol{\Gamma}_{it}$ both include the export dummy and the number of products a firm produces. This constitutes no problem for my estimation, as I am not interested in identifying the coefficients from the control functions. I am solely interested in parametrically estimating the coefficients of $\tilde{\boldsymbol{\phi}}'_{it}$, i.e. the coefficients on the contemporary production factors and their interactions with each other.

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

[41] This also addresses any simultaneity concerns with respect to the price variables entering the right-hand side of my estimation.

dummies, the lagged output price index, lagged market shares, lagged elements of $h_{it}(.)$, and lagged interactions of the output price index with production inputs. Formally this implies:

$$\mathbf{\Upsilon}'_{it} = (J_{it}(.),\ A_{it-1}(.),\ T_{it-1}(.),\ \Psi_{it}(.),\ \boldsymbol{\nu}_{it-1}), \tag{C.7}$$

where for convenience I defined:

$J_{it}(.) = (l_{it}, k_{it}, l_{it}^2, k_{it}^2,\ l_{it}k_{it}, G_{it}, D_{it})$,

$A_{it}(.) = (\ m_{it}, m_{it}^2, l_{it}m_{it}, k_{it}m_{it}, l_{it}k_{it}m_{it}, ms_{it}, \pi_{it})$,

$T_{it}(.) = \left((l_{it}, k_{it}, l_{it}^2, k_{it}^2,\ l_{it}k_{it}, m_{it}, m_{it}^2, l_{it}m_{it}, k_{it}m_{it}, l_{it}k_{it}m_{it}) \times \pi_{it}\right)$,

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

$\boldsymbol{\nu}_{it-1} = (Exp_{it-1}, NumP_{it-1}, w_{it-1})$,

with w_{it} denoting the average wage a firm pays.[42]

Results

Table C.1 and C.2 show median and average output elasticities.[43] In total, I can compute output elasticities for 248,400 firms. Median (mean) output elasticities across all industries equal 0.63 (0.64) 0.30 (0.30) 0.11 (0.11) for intermediates, labor, and capital inputs, respectively.

For 5,418 firms in the data, I estimate negative output elasticities. As negative output elasticities are inconsistent with the production model I assume, I drop these firms from the further analysis.

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[42] The inclusion of output price information on the right-hand side of the production function also helps to address concerns about potential violations of the "scalar unobservability" assumption as discussed in Doraszelski & Jaumandreu (2020).

[43] I follow De Loecker et al. (2016) and use estimates of the price control function to purge remaining input price variation from deflated input expenditures for intermediates and capital when estimating output elasticities.

TABLE C.1

PRODUCTION FUNCTION ESTIMATION:
MEDIAN OUTPUT ELASTICITIES, BY SECTOR

Sector	Number of observations (1)	Intermediate inputs (2)	Labor (3)	Capital (4)	Returns to scale (5)
15 Food products and beverages	29,874	0.66	0.17	0.12	0.95
17 Textiles	8,618	0.67	0.32	0.17	1.14
18 Apparel, dressing, and dyeing of fur	3,236	0.73	0.22	0.12	1.05
19 Leather and leather products	1,923	0.65	0.27	0.14	1.09
20 Wood and wood products	7,229	0.66	0.23	0.09	0.99
21 Pulp, paper, and paper products	7,115	0.69	0.27	0.09	1.05
22 Publishing and printing	5,967	0.57	0.25	0.08	0.88
24 Chemicals and chemical products	15,155	0.69	0.26	0.12	1.09
25 Rubber and plastic products	15,909	0.66	0.25	0.11	0.99
26 Other non-metallic mineral products	13,612	0.62	0.29	0.13	1.07
27 Basic metals	10,178	0.66	0.34	0.06	1.06
28 Fabricated metal products	32,866	0.60	0.32	0.09	1.00
29 Machinery and equipment	40,169	0.62	0.37	0.10	1.08
30 Electrical and optical equipment	1,984	0.62	0.33	0.13	1.09
31 Electrical machinery and apparatus	14,833	0.63	0.30	0.11	1.04
32 Radio, television, and communication	4,380	0.60	0.39	0.13	1.10
33 Medical and precision instruments	10,534	0.57	0.37	0.14	1.09
34 Motor vehicles and trailers	8,815	0.68	0.32	0.10	1.07
35 Transport equipment	3,894	0.62	0.31	0.02	0.96
36 Furniture manufacturing	12,109	0.65	0.32	0.14	1.09
Across all industries	248,400	0.63	0.30	0.11	1.04

Notes: Table C.1 reports median output elasticities calculated after estimating the production function (C.5) for every NACE rev. 1.1 two-digit industry with sufficient observations. Column 1 reports the number of observations used to calculate output elasticities for each industry. Columns 2-4 respectively report median output elasticities for intermediate, labor, and capital inputs. Column 5 reports median returns to scale. All regressions control for time dummies.

TABLE C.2

PRODUCTION FUNCTION ESTIMATION:
AVERAGE OUTPUT ELASTICITIES, BY SECTOR

Sector	Number of observations (1)	Intermediate inputs (2)	Labor (3)	Capital (4)	Returns to scale (5)
15 Food products and beverages	29,874	0.66 (0.11)	0.17 (0.08)	0.12 (0.05)	0.95 (0.06)
17 Textiles	8,618	0.66 (0.10)	0.32 (0.09)	0.17 (0.09)	1.15 (0.11)
18 Apparel, dressing, and dyeing of fur	3,236	0.72 (0.10)	0.23 (0.10)	0.13 (0.06)	1.07 (0.10)
19 Leather and leather products	1,923	0.67 (0.11)	0.28 (0.12)	0.14 (0.08)	1.08 (0.13)
20 Wood and wood products	7,229	0.66 (0.08)	0.23 (0.10)	0.08 (0.05)	0.98 (0.10)
21 Pulp, paper, and paper products	7,115	0.70 (0.09)	0.26 (0.09)	0.09 (0.05)	1.04 (0.08)
22 Publishing and printing	5,967	0.57 (0.08)	0.25 (0.07)	0.08 (0.03)	0.89 (0.08)
24 Chemicals and chemical products	15,155	0.69 (0.08)	0.26 (0.05)	0.12 (0.06)	1.07 (0.08)
25 Rubber and plastic products	15,909	0.66 (0.07)	0.25 (0.08)	0.12 (0.05)	1.02 (0.10)
26 Other non-metallic mineral products	13,612	0.63 (0.07)	0.29 (0.05)	0.13 (0.06)	1.05 (0.08)
27 Basic metals	10,178	0.67 (0.09)	0.34 (0.07)	0.06 (0.04)	1.06 (0.07)
28 Fabricated metal products	32,866	0.60 (0.08)	0.32 (0.10)	0.09 (0.03)	1.01 (0.10)
29 Machinery and equipment	40,169	0.62 (0.08)	0.37 (0.07)	0.10 (0.04)	1.08 (0.10)
30 Electrical and optical equipment	1,984	0.62 (0.05)	0.34 (0.08)	0.13 (0.05)	1.09 (0.04)
31 Electrical machinery and apparatus	14,833	0.63 (0.06)	0.30 (0.07)	0.12 (0.05)	1.05 (0.10)
32 Radio, television, and communication	4,380	0.60 (0.05)	0.38 (0.08)	0.15 (0.08)	1.13 (0.12)
33 Medical and precision instruments	10,534	0.56 (0.03)	0.38 (0.05)	0.14 (0.01)	1.08 (0.08)
34 Motor vehicles and trailers	8,815	0.68 (0.10)	0.32 (0.09)	0.10 (0.07)	1.10 (0.11)
35 Transport equipment	3,894	0.63 (0.09)	0.31 (0.05)	0.02 (0.05)	0.95 (0.02)
36 Furniture manufacturing	12,109	0.65 (0.09)	0.31 (0.10)	0.14 (0.08)	1.11 (0.15)
Across all industries	248,400	0.64 (0.09)	0.30 (0.10)	0.11 (0.06)	1.04 (0.11)

Notes: Table C.2 reports average output elasticities calculated after estimating the production function (C.5) for every NACE rev. 1.1 two-digit industry with sufficient observations. Column 1 reports the number of observations used to calculate output elasticities for each industry. Columns 2-4 respectively report average output elasticities for intermediate, labor, and capital inputs. Column 5 reports average returns to scale. Associated standard deviations are reported in brackets. All regressions control for time dummies.

Appendix D: Calculation of the capital stock

The following approach closely follows the Appendix of Bräuer, Mertens, & Slavtchev (2019), who, similar to Mueller (2008), use information on the expected lifetime of capital goods to calculate an industry- and time-specific depreciation rate of capital. Having calculated this depreciation rate, one can use a perpetual inventory method to calculate a capital stock series for every firm in the data:

(I.1) $$K_{it} = K_{it-1}\left(1 - \alpha_{jt-1}\right) + I_{it-1}.$$

K_{it}, α_{jt}, and I_{it} respectively denote the capital stock, the depreciation rate of capital in industry j, and investment. I will now explain how to derive an expression for α_{jt}.

The statistical office of Germany supplies information on the expected lifetime of capital goods bought in period t, separately for buildings and equipment. As everything what follows is equivalent for both types of capital goods, let us abstract from different capital good types and denote the expected lifetime of any capital good bought in period t simply by D_t. Let us further assume that the depreciation rate of a capital good stays constant throughout its lifetime. Hence, the average (or expected) lifetime of a capital stock bought in period $t = 0$ can be defined as:

(I.2) $$D_0 = \frac{1}{K_0}\sum\nolimits_0^{\infty}(\alpha K_t)t,$$

where the sum is taken over all periods t. αK_t denotes the amount of depreciated capital in period t. Assuming a linear capital depreciation, consistent with (I.1), implies: $K_t = K_0(1 - \delta_0)^t$. Substituting this into (I.2) and switching to continuous time gives:

(I.3) $$D_0 = \frac{1}{K_0}\int_0^{\infty}(\alpha K_0(1 - \alpha)^t)t\,dt.$$

After rearranging we have:

(I.4) $$D_0 = \alpha \int_0^\infty (1-\alpha)^t t \, dt.$$

Partial integration gives:

(I.5) $$D_0 = \alpha \left[\frac{(1-\alpha)^t}{\ln(1-\alpha)} t \right]_0^\infty - \alpha \int_0^\infty \frac{(1-\alpha)^t}{\ln(1-\alpha)} dt.$$

Note that the first term on the right-hand side of (I.5) equals zero because $0 < \alpha < 1$. Integrating the remaining expression gives:

(I.6) $$D_0 = \frac{\alpha}{\ln(1-\alpha) * \ln(1-\alpha)}.$$

Given that the expected lifetime, D_0, is known, (I.6) can be solved numerically.

Recap that the statistical office reports the expected lifetime of capital goods separately for buildings and equipment. Hence, I calculate a separate depreciation rate for each of those capital good types. To receive a single industry-specific depreciation rate, I weight the depreciation rates for buildings and equipment respectively with the industry-level share of building capital in total capital and equipment capital in total capital and sum up (this information is also supplied by the statistical office). For the practical implementation, I assume that the depreciation rate of a firm's whole capital stock equals the depreciation rate of newly purchased capital. Thus, for every industry and year I compute:

(I.7) $$\alpha_{jt} = \alpha_{jt}^{Build} \frac{K_{jt}^{Build}}{K_{jt}} + \alpha_{jt}^{Equip} \frac{K_{jt}^{Equip}}{K_{jt}},$$

where the superscript indicates whether the variable refers to a building or equipment specific variable. K_{jt}^{Build}, K_{jt}^{Equip}, and $K_{jt} = K_{jt}^{Build} + K_{jt}^{Equip}$ respectively denote the total building capital stock, the total equipment capital stock, and the total capital stock of industry j in period t. Having calculated this depreciation rate, I use equation (I.1) to calculate firm-specific capital series.

To calculate the first capital stock of every capital series, I divide the reported tax depreciation (given in my data) by the depreciation rate. I do not use the tax depreciation variable in my law of motion because reported tax depreciations vary due to state induced tax incentives and, therefore, do not necessary reflect the true amount of depreciated capital (e.g. House & Shapiro (2008)). Given that firms likely report too high values of depreciated capital due to such incentives, the first capital stock in each of my capital series is likely an overestimate of the true capital stock used in the firm's production activities. Over longer periods, however, observed investment decisions gradually receive a larger weight in the estimated capital stocks. This mitigates the impact of the first capital stock over time. Given that I estimate very reasonable output elasticities for capital (see the online Appendix C), I am confident that my capital variables reliably reflect firms' true capital stocks.[44]

[44] Given that firms likely overstate their capital depreciation, my capital stocks are likely a closer approximation of the true capital stock used in firms' production activities than existing capital measures based on book values.

Appendix E: Core results using a constant and time-varying Cobb-Douglas production model

Appendix E.1: Time-constant Cobb-Douglas specification

This section replicates core results using a simple Cobb-Douglas production model with industry-specific and time constant output elasticities. The key insight from this replication is that all my results are robust to using this alternative production.

The Cobb-Douglas production model

The estimation routine of the Cobb-Douglas production model closely follows the procedure described in the online Appendix C. The only differences are that i) I omit the translog interactions and higher order terms of production inputs captured in $\boldsymbol{\phi}_{it}'$ and ii) the price control function $B_{it}(.)$ now contains no interaction between production inputs and any other element of $B_{it}(.)$, which follows from the Cobb-Douglas structure (see De Loecker et al. (2016)). Formally, the Cobb-Douglas production model I take to the data is:

(E.1) $$q_{it} = \theta^L l_{it} + \theta^M m_{it} + \theta^K k_{it} + B_{it}(.) + h_{it}(.) + \xi_{it} + \varepsilon_{it},$$

where $B_{it}(.) = B_{it}(\pi_{it}, ms_{it}, G_{it}, D_{it})$ and the notation is consistent with the online Appendix C. As in the online Appendix C, I approximate $h_{it}(.) = h_{it}(e_{it-1}, k_{it-1}, l_{it-1}, EX_{it-1}, NumP_{it-1}, w_{it-1})$ with a third order polynomial in e_{it-1}, k_{it-1}, and, l_{it-1} and add EX_{it-1}, $NumP_{it-1}$, and w_{it-1} linearly.

In line with the translog-model described in online Appendix C, the identifying moments are based on variables that enter $h_{it}(.)$ as lagged values, lagged values of ms_{it} and π_{it}, contemporary values of G_{it} and D_{it}, contemporary values of k_{it} and l_{it}, and the lagged value of m_{it}.

Key results using the Cobb-Douglas production model

Figure E.1 shows the cross-sectional dispersion of wages and marginal revenue products of labor. Again, the distribution of marginal revenue products of labor exceeds the distribution of wages on the left and right side.

DISTRIBUTION OF MARGINAL REVENUE PRODUCTS OF LABOR AND WAGES ACROSS FIRMS USING A COBB-DOUGLAS MODEL

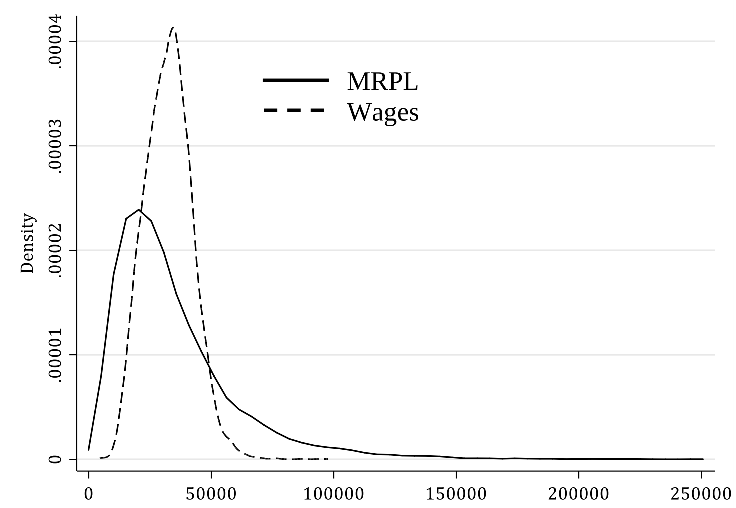

FIGURE E.1 – Distribution of marginal revenue products of labor and average wages across firms in 1995. Results for other years and all years pooled look similar. Expressed in values of 1995. Cobb-Douglas production model. Germany's manufacturing sector. Sample firms.

Table E.1 reproduces Table 2 of the main text and shows that, also under a Cobb-Douglas model, i) MRPL dispersion increases much stronger than wage dispersion and ii) the upper half of the MRPL distribution is particularly contributing to the enormous increase in MRPL dispersion.

TABLE E.1

SELECTED PERCENTILE DIFFERENCES FOR FIRM WAGES AND MARGINAL REVENUE PRODUCTS OF LABOR OVER TIME USING A COBB-DOUGLAS PRODUCTION FUNCTION, ENTIRE MANUFACTURING SECTOR

	Percentile differences firm wages			Percentile differences firm MRPL			
Year	90-10	90-50	50-10	90-10	90-50	50-10	Diff. between column 4 and 1
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1995	24,525€	12,041€	12,484€	55,307€	38,094€	17,213€	30,782€
2000	27,148€	13,492€	13,656€	63,031€	44,070€	18,961€	35,884€
2005	29,141€	14,766€	14,375€	73,221€	51,476€	21,746€	44,080€
2010	28,869€	15,641€	13,228€	76,672€	55,450€	21,223€	47,803€
2016	30,578€	16,687€	13,891€	78,523€	56,506€	22,018€	47,946€

Notes: Table E.1 reports 90-10, 90-50, and 50-10 percentile differences of the firm distribution for wages and marginal revenue products of labor when using a Cobb-Douglas production model to calculate marginal revenue products of labor. Wages and marginal revenue products of labor are expressed in values of 1995. Germany's manufacturing sector. Sample firms.

Finally, Table E.2 replicates Table 4 of the main text, showing that, also under a Cobb-Douglas production model, I find i) that along the wage, size, and MRPL distributions, labor market power, wages, productivity, and marginal revenue products of labor are increasing, ii) that there is an enormous gap between wages and MRPL for the largest, highest-paying, highest-MRPL firms which heavily contributes to the MRPL distribution being much more dispersed than the wage distribution, and iii) that large, high-paying, high-MRPL firms generate a substantial amount of rents from labor markets while being active in comparably competitive product markets.[45]

[45] Consistent with the results of the main text, I find that marginal revenue products of labor and labor market power are strongly growing for the upper ventiles of these distributions when using the Cobb-Douglas production model.

TABLE E.2

DISPERSION IN WAGES, MARGINAL REVENUE PRODUCTS OF LABOR, AND LABOR MARKET POWER, BY SECTOR USING A COBB-DOUGLAS PRODUCTION MODEL

	Mean values for firm wage ventiles					Mean values for number of employees ventiles					Mean values for MRPL ventiles				
	Wage	MRPL	Labor prod.	PMP	LMP	Wage	MRPL	Labor prod.	PMP	LMP	Wage	MRPL	Labor prod.	PMP	LMP
Ventiles (P = percentile)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Firms ≤ 5P	13,487€	10,334€	9.78	1.21	0.76	29,051€	28,711€	10.36	1.19	0.97	16,717€	5,425€	9.91	1.50	0.34
Firms > 5P and ≤ 10P	17,899€	17,653€	10.02	1.16	0.98	28,957€	30,272€	10.37	1.17	1.02	22,919€	9,799€	10.16	1.46	0.47
Firms > 10P and ≤ 15P	20,768€	22,848€	10.18	1.13	1.10	29,139€	31,546€	10.37	1.16	1.06	26,185€	13,004€	10.27	1.38	0.55
Firms > 15P and ≤ 20P	22,950€	26,189€	10.27	1.11	1.14	29,593€	31,912€	10.40	1.15	1.06	27,956€	15,704€	10.33	1.30	0.61
Firms > 20P and ≤ 25P	24,841€	28,561€	10.34	1.11	1.15	30,019€	33,330€	10.41	1.14	1.09	29,116€	18,176€	10.37	1.25	0.68
Firms > 25P and ≤ 30P	26,535€	30,697€	10.39	1.11	1.16	30,590€	34,296€	10.45	1.13	1.10	30,039€	20,581€	10.40	1.20	0.74
Firms > 30P and ≤ 35P	28,121€	32,583€	10.45	1.11	1.16	30,679€	35,071€	10.45	1.13	1.11	30,949€	23,008€	10.44	1.16	0.80
Firms > 35P and ≤ 40P	29,625€	34,393€	10.49	1.11	1.16	31,405€	36,684€	10.48	1.11	1.14	31,700€	25,467€	10.47	1.13	0.86
Firms > 40P and ≤ 45P	31,069€	36,076€	10.53	1.11	1.16	31,580€	37,896€	10.50	1.11	1.16	32,682€	28,020€	10.51	1.10	0.92
Firms > 45P and ≤ 50P	32,476€	38,305€	10.55	1.11	1.18	31,950€	38,529€	10.52	1.10	1.17	33,583€	30,714€	10.53	1.08	0.98
Firms > 50P and ≤ 55P	33,885€	39,815€	10.62	1.10	1.18	32,551€	39,157€	10.54	1.10	1.18	34,498€	33,615€	10.59	1.06	1.04
Firms > 55P and ≤ 60P	35,311€	42,403€	10.66	1.09	1.20	33,254€	41,392€	10.57	1.09	1.21	35,211€	36,892€	10.62	1.03	1.12
Firms > 60P and ≤ 65P	36,741€	44,257€	10.70	1.09	1.20	33,420€	42,234€	10.57	1.08	1.23	36,111€	40,644€	10.65	1.01	1.20
Firms > 65P and ≤ 70P	38,232€	45,929€	10.74	1.10	1.20	34,276€	44,533€	10.61	1.07	1.27	36,938€	44,936€	10.68	0.99	1.30
Firms > 70P and ≤ 75P	39,830€	48,961€	10.78	1.09	1.23	35,151€	46,564€	10.64	1.07	1.29	37,881€	49,925€	10.73	0.96	1.41
Firms > 75P and ≤ 80P	41,580€	52,163€	10.81	1.08	1.25	36,156€	48,302€	10.65	1.06	1.31	38,945€	55,941€	10.77	0.94	1.53
Firms > 80P and ≤ 85P	43,639€	56,982€	10.86	1.07	1.30	37,828€	51,092€	10.70	1.05	1.33	39,773€	63,814€	10.86	0.92	1.71
Firms > 85P and ≤ 90P	46,147€	62,238€	10.91	1.06	1.35	39,619€	53,385€	10.76	1.05	1.32	41,404€	74,832€	10.92	0.89	1.92
Firms > 90P and ≤ 95P	49,707€	70,928€	10.97	1.04	1.42	40,937€	56,685€	10.76	1.04	1.34	42,794€	92,332€	11.02	0.86	2.29
Firms > 95P	58,393€	85,677€	11.09	1.03	1.46	45,379€	66,405€	10.90	1.01	1.42	45,824€	144,211€	11.10	0.81	3.29
Overall average	33,560€	41,347€	10.55	1.10	1.19	33,560€	41,347€	10.55	1.10	1.19	33,560€	41,347€	10.55	1.10	1.19
Total observations	242,982	242,982	222,215	242,982	242,982	242,982	242,982	222,215	242,982	242,982	242,982	242,982	222,215	242,982	242,982

Notes: Table E.2 reports averages for wages, marginal revenue products of labor, labor productivity, firms' product market power, and firms' labor market power for each ventile of the firm wage, size (employment), and MRPL distributions. Results are based on a Cobb-Douglas production model. Wages and marginal revenue products of labor are expressed in values of 1995. Germany's manufacturing sector. Sample firms.

Appendix E.2: Time-varying translog specification

This section replicates core results using a more sophisticated model that estimates the baseline translog production model by individual years using moving time-intervals. I still estimate the production function separately for each two-digit-industries. Additionally, I estimate the industry-specific production functions now also separately for moving 5-year intervals. I then place the estimates in the middle-year of each interval. The first estimation step takes the years 1995-1999 and estimates coefficients for 1997, the second step takes the years 1996-2000 and estimates coefficients for 1998 and so on. As consequence, I drop the first and last two years of the sample. Yet, this time-varying specification is much more flexible and accounts for biased-technological change that might bias my baseline estimates.

As shown below, all my results hold also for this alternative production model.

Key results using the time-varying translog model

Figure E.4 shows the cross-sectional dispersion of wages and marginal revenue products of labor. As before, the firm MRPL distribution exceeds the firm wage distribution on the left and right side.[46]

[46] Figure E.4 shows distributions for the year 2005 because 1995 is dropped in this specification.

DISTRIBUTION OF MARGINAL REVENUE PRODUCTS OF LABOR AND WAGES ACROSS FIRMS USING A COBB-DOUGLAS MODEL

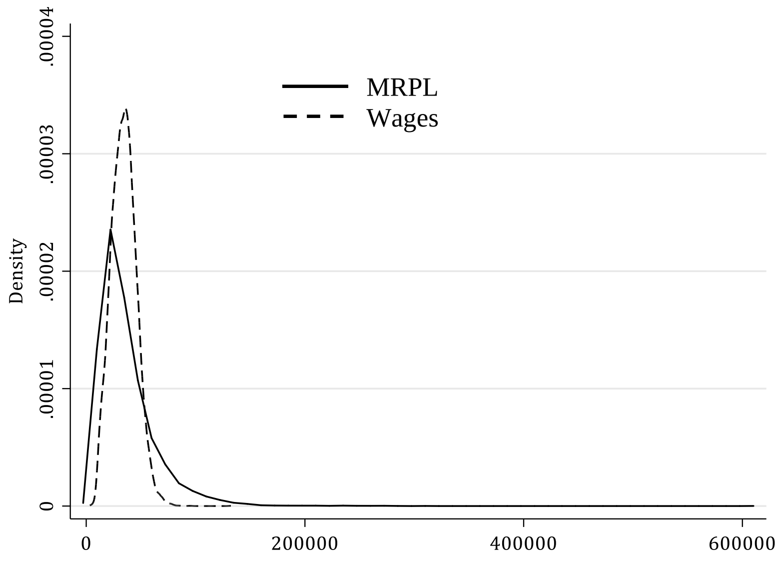

FIGURE E.4 – Distribution of marginal revenue products of labor and average wages across firms in 2005. Results for other years and all years pooled look similar. Expressed in values of 2005. Time-varying translog production model. Germany's manufacturing sector. Sample firms.

Table E.1 reproduces Table 2 of the main text and shows that, also the under the time-varying translog model, i) MRPL dispersion increases much stronger than wage dispersion and ii) the upper half of the MRPL distribution is particularly contributing to the enormous increase in MRPL dispersion.

TABLE E.3

SELECTED PERCENTILE DIFFERENCES FOR FIRM WAGES AND MARGINAL REVENUE PRODUCTS OF LABOR OVER TIME USING A TIME-VARYING TRANSLOG PRODUCTION FUNCTION, ENTIRE MANUFACTURING SECTOR

	Percentile differences firm wages			Percentile differences firm MRPL			
Year	90-10	90-50	50-10	90-10	90-50	50-10	Diff. between column 4 and 1
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1997	25,070€	12,044€	13,026€	39,908€	25,579€	14,329€	14,838€
2000	27,148€	13,492€	13,656€	46,879€	31,278€	15,601€	19,731€
2005	29,141€	14,766€	14,375€	56,170€	38,483€	17,687€	27,029€
2010	28,869€	15,641€	13,228€	63,829€	44,908€	18,921€	34,960€
2014	30,180€	16,098€	14,082€	60,414€	43,023€	17,392€	30,234€

Notes: Table E.3 reports 90-10, 90-50, and 50-10 percentile differences of the firm distribution for wages and marginal revenue products of labor when using a time-varying translog production model to calculate marginal revenue products of labor. Wages and marginal revenue products of labor are expressed in values of 1995. Germany's manufacturing sector. Sample firms.

Finally, Table E.4 replicates Table 4 of the main text using the time-varying translog model, showing that, I again find i) that along the wage, size, and MRPL distributions, labor market power, wages, productivity, and marginal revenue products of labor are increasing, ii) that there is an enormous gap between wages and MRPL for the largest, highest-paying, highest-MRPL firms which heavily contributes to the MRPL distribution being much more dispersed than the wage distribution, and iii) that large, high-paying, high-MRPL firms generate a substantial amount of rents from labor markets while selling on competitive product markets.[47]

[47] Consistent with the results of the main text, I find that marginal revenue products of labor and labor market power are strongly growing for the upper ventiles of these distributions when using the time-varying translog production model.

TABLE E.4

DISPERSION IN WAGES, MARGINAL REVENUE PRODUCTS OF LABOR, AND LABOR MARKET POWER, BY SECTOR USING A COBB-DOUGLAS PRODUCTION MODEL

	Mean values for firm wage ventiles					Mean values for number of employees ventiles					Mean values for MRPL ventiles				
	Wage	MRPL	Labor prod.	PMP	LMP	Wage	MRPL	Labor prod.	PMP	LMP	Wage	MRPL	Labor prod.	PMP	LMP
Ventiles (P = percentile)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Firms ≤ 5P	13,487€	11,982€	9.78	1.01	0.90	29,051€	18,635€	10.36	1.14	0.67	20,408€	6,693€	9.98	1.19	0.39
Firms > 5P and ≤ 10P	17,899€	17,094€	10.02	1.04	0.96	28,957€	20,640€	10.37	1.13	0.74	22,593€	10,662€	10.09	1.16	0.54
Firms > 10P and ≤ 15P	20,768€	20,765€	10.18	1.06	1.00	29,139€	21,804€	10.37	1.12	0.77	25,284€	13,452 €	10.19	1.17	0.59
Firms > 15P and ≤ 20P	22,950€	23,092€	10.27	1.06	1.01	29,593€	23,170€	10.40	1.12	0.80	26,785€	15,813€	10.26	1.16	0.65
Firms > 20P and ≤ 25P	24,841€	24,731€	10.34	1.07	1.00	30,019€	24,394€	10.41	1.12	0.83	28,054€	17,910€	10.34	1.15	0.70
Firms > 25P and ≤ 30P	26,535€	26,682€	10.39	1.08	1.01	30,590€	25,418€	10.45	1.12	0.85	29,234€	19,915€	10.36	1.14	0.74
Firms > 30P and ≤ 35P	28,121€	28,091€	10.45	1.09	1.00	30,679€	26,966€	10.45	1.11	0.89	30,168€	21,898€	10.43	1.13	0.78
Firms > 35P and ≤ 40P	29,625€	29,867€	10.49	1.09	1.01	31,405€	28,714€	10.48	1.10	0.93	31,084€	23,908€	10.46	1.12	0.83
Firms > 40P and ≤ 45P	31,069€	30,639€	10.53	1.10	0.99	31,580€	30,072€	10.50	1.10	0.96	31,962€	25,979€	10.50	1.11	0.87
Firms > 45P and ≤ 50P	32,476€	32,518€	10.55	1.10	1.00	31,950€	31,470€	10.52	1.10	1.00	32,969€	28,173€	10.53	1.10	0.91
Firms > 50P and ≤ 55P	33,885€	34,082€	10.62	1.10	1.01	32,551€	32,866€	10.54	1.09	1.02	33,823€	30,564€	10.58	1.09	0.96
Firms > 55P and ≤ 60P	35,311€	36,508€	10.66	1.10	1.03	33,254€	35,276€	10.57	1.09	1.07	34,687€	33,204€	10.62	1.08	1.02
Firms > 60P and ≤ 65P	36,741€	38,252€	10.70	1.10	1.04	33,420€	36,495€	10.57	1.07	1.10	35,652€	36,096€	10.66	1.07	1.08
Firms > 65P and ≤ 70P	38,232€	40,220€	10.74	1.11	1.05	34,276€	38,931€	10.61	1.07	1.14	36,913€	39,428€	10.71	1.06	1.14
Firms > 70P and ≤ 75P	39,830€	43,007€	10.78	1.10	1.08	35,151€	42,146€	10.64	1.07	1.21	38,048€	43,223€	10.75	1.05	1.20
Firms > 75P and ≤ 80P	41,580€	46,233€	10.81	1.10	1.11	36,156€	44,855€	10.65	1.06	1.25	39,395€	47,804€	10.79	1.04	1.28
Firms > 80P and ≤ 85P	43,639€	50,675€	10.86	1.10	1.16	37,828€	48,742€	10.70	1.06	1.29	40,577€	53,602€	10.85	1.02	1.39
Firms > 85P and ≤ 90P	46,147€	54,988€	10.91	1.11	1.19	39,619€	54,327€	10.76	1.05	1.37	42,223€	61,729€	10.93	1.00	1.54
Firms > 90P and ≤ 95P	49,707€	61,931€	10.97	1.10	1.24	40,937€	59,977€	10.76	1.04	1.45	44,262€	74,661€	11.04	0.98	1.77
Firms > 95P	58,393€	74,173€	11.09	1.11	1.26	45,379€	77,475€	10.90	1.02	1.68	47,212€	120,082€	11.20	0.94	2.67
Overall average	33,560€	36,234€	10.55	1.09	1.05	33,560€	36,234€	10.55	1.09	1.05	33,566€	36,234€	10.55	1.09	1.05
Total observations	242,982	200,054	222,215	200,054	200,054	242,982	200,054	222,215	200,054	200,054	200,054	200,054	182,262	200,054	200,054

Notes: Table E.4 reports averages for wages, marginal revenue products of labor, labor productivity, firms' product market power, and firms' labor market power for each ventile of the firm wage, size (employment), and MRPL distributions. Results are based on a time-varying translog production model. Wages and marginal revenue products of labor are expressed in values of 1995. Germany's manufacturing sector. Sample firms.

Appendix F: Changes in product market power for top firms

In the main text, I show that high-paying, large, and high-MRPL firms possess high labor market power, that, although only slightly rising, allow these firms to generate increasingly large rents from labor markets. This is because labor market power is defined as the ratio between wages and marginal revenue products of labor. Hence, even if wages and marginal revenue products of labor would grow proportionally (and labor market power would stay constant), the total Euro level of rents would increase for a given percentage wedge between wages and marginal revenue products of labor (i.e. for a given level of labor market power). Moreover, starting from a high level of firm-side labor market power, even a decrease in firm-side labor market power can lead to an increase in total labor market rents of firms (i.e. an increase in the Euro level of rents), if wages and marginal revenue products of labor grow sufficiently strong.

In contrast and as I show below in Table F.1, product market power levels of these top firms, although increasing, stay on, compared to labor market power, much lower levels. Hence, also over time, top firms generate particularly high rents on labor markets, while being active on comparably competitive product markets.

TABLE F.1

AVERAGE PRODUCT AND LABOR MARKET POWER FOR HIGH WAGE, LARGE, AND HIGH-MRPL FIRMS,
OVER TIME

	Product market power			Labor market power		
Year	High-wage firms (1)	Large firms (2)	High-MRPL firms (3)	High-wage firms (4)	Large firms (5)	High-MRPL firms (6)
1995	1.08	0.99	0.94	1.13	1.55	2.10
1996	1.10	1.01	0.94	1.07	1.48	2.03
1997	1.09	1.01	0.95	1.13	1.51	2.06
1998	1.10	1.01	0.95	1.14	1.53	2.07
1999	1.12	1.03	0.96	1.08	1.48	2.07
2000	1.11	1.02	0.96	1.13	1.57	2.15
2001	1.10	1.01	0.96	1.15	1.59	2.15
2002	1.10	1.02	0.96	1.15	1.54	2.07
2003	1.11	1.02	0.96	1.12	1.52	2.11
2004	1.11	1.03	0.98	1.16	1.57	2.14
2005	1.13	1.03	0.97	1.18	1.61	2.23
2006	1.10	1.03	0.98	1.30	1.67	2.35
2007	1.13	1.03	0.98	1.30	1.72	2.49
2008	1.12	1.02	0.97	1.32	1.72	2.49
2009	1.09	1.01	0.95	1.20	1.53	2.24
2010	1.12	1.04	0.97	1.26	1.60	2.36
2011	1.13	1.03	0.97	1.31	1.73	2.53
2012	1.12	1.03	0.97	1.29	1.64	2.44
2013	1.11	1.03	0.97	1.29	1.58	2.34
2014	1.12	1.04	0.98	1.25	1.56	2.29
2015	1.12	1.06	0.98	1.24	1.54	2.23
2016	1.14	1.07	1.00	1.23	1.52	2.15

Notes: Table F.1 reports average product and labor market power levels for high-wage, large, and high-MRPL firms. These firms are located in the last ventiles of the respective firm wage, size, and MRPL distributions. Germany’s manufacturing sector. Sample firms.

Appendix G: Additional results from the CompNet database

Table G.1 shows firm wage and MRPL dispersion for each year and country of my additional analysis based on the CompNet data.

TABLE G.1

MRPL AND FIRM WAGE DISPERSION IN SEVERAL EUROPEAN COUNTRIES, BY YEARS								
	ITALY		SPAIN		BELGIUM		FINLAND	
Year	90-10 percentile differences, wages	90-10 percentile differences, MRPL	90-10 percentile differences, wages	90-10 percentile differences, MRPL	90-10 percentile differences, wages	90-10 percentile differences, MRPL	90-10 percentile differences, wages	90-10 percentile differences, MRPL
1999	-	-	-	-	-	-	19,954.08€	57,629.34€
2000	-	-	-	-	29,014.35€	70,942.14€	20,657.00€	57,603.38€
2001	-	-	-	-	28,963.21€	71,583.11€	21,142.82€	58,731.41€
2002	-	-	-	-	30,446.58€	73,712.38€	21,179.58€	55,937.26€
2003	-	-	-	-	30,901.23€	75,483.64€	20,942.96€	57,209.57€
2004	-	-	-	-	31,165.62€	81,653.99€	21,204.05€	61,630.82€
2005	-	-	-	-	30,938.07€	86,814.51€	21,521.68€	61,008.06€
2006	27,159.22€	73,004.53€	-	-	31,015.46€	90,310.05€	23,048.82€	61,404.82€
2007	26,747.51€	74,604.03€	-	-	32,057.76€	85,123.49€	23,767.63€	55,960.55€
2008	26,545.27€	69,960.55€	26,225.37€	72,220.76€	32,132.50€	84,241.50€	23,649.39€	56,649.85€
2009	26,136.60€	60,332.82€	26,571.77€	66,299.33€	33,611.81€	79,946.02€	23,240.42€	49,035.80€
2010	27,473.21€	64,570.56€	26,088.27€	67,326.90€	33,559.90€	82,139.89€	24,162.06€	51,727.84€
2011	28,170.43€	65,827.23€	26,561.20 €	66,474.63€	33,239.06€	82,092.47€	24,381.52€	53,178.49€
2012	28,204.01€	61,984.96€	26,502.22€	63,641.45€	33,104.87€	79,926.28€	24,225.14€	52,869.85€
2013	28,585.35€	60,896.52€	26,564.31€	63,254.32€	34,189.16€	83,158.77€	24,421.36€	52,492.73€
2014	29,032.27€	61,690.29€	27,121.66€	66,878.54€	34,472.20€	86,537.39€	23,571.35€	50,829.68€
2015	29,446.93€	62,981.27€	26,866.34€	68,944.20€	33,518.12€	84,268.16€	24,931.34€	53,251.13€
2016	29,773.42€	60,776.38€	26,183.24€	66,862.27€	33,915.03€	88,626.77€	24,831.02€	54,581.45€
2017	30,290.88€	61,273.95€	25,793.23€	66,512.84€	34,069.98€	89,900.74€	24,384.90€	54,545.00€
2018	30,285.76€	61,108.48€	24,787.27€	65,687.89€	34,123.67€	89,551.90€	24,479.71€	55,317.32€
2019	-	-	-	-	-	-	25,377.64€	54,971.00€
	SLOVENIA		POLAND		CROATIA		SWITZERLAND	
Year	90-10 percentile differences, wages	90-10 percentile differences, MRPL	90-10 percentile differences, wages	90-10 percentile differences, MRPL	90-10 percentile differences, wages	90-10 percentile differences, MRPL	90-10 percentile differences, wages	90-10 percentile differences, MRPL
2002	22,398.18€	49,394.17€	17,511.29€	30,807.77€	14,356.11€	79,830.81€	-	-
2003	21,680.64€	46,584.64€	15,812.31€	31,483.08€	13,950.90€	76,584.95€	-	-
2004	22,110.07€	48,460.40€	15,318.91€	30,866.18€	14,365.00€	78,946.67€	-	-
2005	22,447.19€	46,311.31€	17,133.11€	32,114.98€	15,442.80€	83,418.41€	-	-
2006	23,042.32€	50,859.58€	18,330.49€	34,303.19€	15,863.43€	83,372.63€	-	-
2007	23,246.89€	53,932.63€	20,237.87€	36,998.67€	16,217.33€	82,712.15€	-	-
2008	22,815.98€	60,682.90€	22,816.11€	40,021.22€	16,573.60€	81,621.25€	-	-
2009	22,636.32€	54,455.54€	18,424.09€	31,791.10€	16,444.36€	69,990.63€	37,835.32	56,202.70
2010	22,450.27€	54,461.01€	19,795.63€	35,875.60€	16,240.90€	64,717.85€	43,004.75	64,093.52
2011	22,091.32€	56,548.06€	20,059.07€	37,464.29€	16,080.06€	64,540.87€	44,145.64	69,641.30
2012	21,787.93€	55,131.87€	20,003.87€	36,589.01€	15,595.56€	60,936.05€	42,820.62	65,648.80
2013	21,125.82€	54,177.36€	20,053.17€	37,170.27€	15,052.94€	59,256.19€	41,620.92	63,668.73
2014	21,083.48€	54,828.07€	20,600.83€	38,362.32€	15,341.51€	60,400.16€	44,272.83	64,772.31
2015	22,088.85€	53,333.79€	21,430.41€	40,307.91€	15,755.62€	62,012.54€	49,070.58	68,380.03
2016	22,470.45€	54,856.91€	21,243.58€	38,674.90€	16,133.39€	63,504.08€	49,562.57	70,676.41
2017	22,573.04€	57,516.24€	22,335.07€	41,517.30€	16,154.76€	62,559.54€	47,139.84	67,396.78
2018	22,755.96€	59,704.49€	22,971.29€	42,899.89€	16,330.44€	66,389.72€	48,051.41	71,828.47
2019	23,014.30€	56,972.38€	23,044.56€	42,866.73€	16,364.01€	68,809.77€	-	-

Notes: Table G.1 reports 90-10 percentile differences for firms' average wages and MRPL for each year and each country of the CompNet data sample I use.

TABLE G.1 CONTINUED				
	DENMARK		SWEDEN	
Year	90-10 percentile differences, wages	90-10 percentile differences, wages	90-10 percentile differences, wages	90-10 percentile differences, MRPL
2003	-	-	30,201.66€	158,848.20€
2004	29,922.73€	84,237.13€	29,281.38€	148,682.20€
2005	29,284.78€	105,036.20€	30,017.14€	167,358.80€
2006	30,052.34€	117,294.00€	31,069.19€	149,711.30€
2007	30,654.84€	114,418.50€	30,943.08€	164,851.30€
2008	33,469.91€	110,466.50€	30,429.10€	153,374.60€
2009	36,723.03€	99,148.64€	28,419.86€	133,368.00€
2010	35,379.84€	93,871.31€	31,098.51€	141,954.00€
2011	34,202.65€	104,447.20€	32,621.71€	145,220.70€
2012	35,012.13€	106,744.70€	34,857.54€	155,572.70€
2013	34,837.18€	96,498.20€	36,480.70€	148,713.90€
2014	34,961.21€	96,661.84€	34,746.21€	148,316.40€
2015	35,527.38€	98,859.66€	35,350.96€	153,285.60€
2016	35,915.50€	93,157.76€	34,335.40€	153,225.40€
2017	-	-	33,739.38€	155,317.00€
2018	-	-	31,236.79€	146,116.20€
2019	-	-	31,656.54€	122,025.50€

Notes: Table G.1 reports 90-10 percentile differences for firms' average wages and MRPL for each year and each country of the CompNet data sample I use.

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Halle Institute for Economic Research –
Member of the Leibniz Association

Kleine Maerkerstrasse 8
D-06108 Halle (Saale), Germany

Postal Adress: P.O. Box 11 03 61
D-06017 Halle (Saale), Germany

Tel +49 345 7753 60
Fax +49 345 7753 820

www.iwh-halle.de

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