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Do Larger Firms Have Higher Markups?

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Do Larger Firms Have Higher Markups?*

Abstract

Several models posit a positive cross-sectional correlation between markups and firm size, which, among others, characterizes misallocation, factor shares, and gains from trade. Yet, taking labor market power into account in markup estimation, we show that larger firms have lower markups. This correlation turns positive only after conditioning on wage markdowns, suggesting interactions between product and labor market power. Our findings are robust to common criticism (e.g., price bias) and hold across 19 European countries. We discuss the resulting implications and highlight studying input and output market power within an integrated framework as an important next step for future research.

Keywords: firm size, markdowns, market power, markups

JEL classification: J42, L11, L13, L25

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1 Introduction

Do larger firms have higher markups? If we consult modern economic theories and standard models alike, the answer is almost always "yes".[1] This is not surprising. Intuitively, larger firms have a more dominant market position and could thus more easily influence prices. Formally, also Marshall's second law of demand states that the price elasticity of demand falls with the quantity consumed (Marshall (1936), Mayer et al. (2021)).

The cross-sectional correlation between markups and firm size is a key outcome in many economic models featuring firm-level markup heterogeneity. Among others, this correlation characterizes misallocation in the economy, aggregate profit shares (Autor et al. (2020)), optimal policies (e.g., Edmond et al. (2022)), and potential gains from competition (Dhingra & Morrow (2019), Arkolakis et al. (2019), Mayer et al. (2021)). It is therefore key to understand whether the data can actually support that larger firms charge higher markups.

In order to test this hypothesis, we follow a dual approach. Firstly, we estimate a rich translog production function on a unique sample of German manufacturing firms, whose prices and quantities are observed, to obtain output elasticities which do not suffer from the so-called "price bias".[2] From that, we derive a clean measure

[1] This holds for old, standard models, like Cournot (1838), and recent papers, e.g., Atkeson & Burstein (2008), Melitz & Oattaviano (2008), Edmond et al. (2015, 2022), Parenti (2018), Boar & Midrigan (2019), De Loecker et al. (2020), Burstein et al. (2020), Peters (2020), Tong & Ornaghi (2021), Hubmer & Restrepo (2022), Bao et al. (2022), Macedoni & Weinberger (2022).

[2] For discussions on the price bias in production function estimation, see De Loecker et al. (2016), Bond et al. (2021), and De Ridder et al. (2022).

of markups using the approach of De Loecker & Warzynski (2012) and document a striking result: contrary to most existing theories, we find that larger firms charge *lower* markups within narrowly defined industries and product markets.

Secondly, we exploit that markups can be compared across firms within industries without estimating output elasticities, if the production function is assumed to be Cobb-Douglas. Using this simplified yet widely applied specification, we test the markup-size relationship on a larger sample of European firms from 19 countries covering almost all economic sectors and confirm our previous result for every country examined.

These findings might appear to contradict some existing work.[3] Yet, there are two explanations for this apparent contradiction. First, several recent studies estimate markup expressions that jointly capture firms' labor and product market power. Particularly, if researchers rely on firms' labor input decisions to estimate markups, their results will be biased whenever labor markets are not perfectly competitive. Relying on such markup expressions makes it unclear whether studied associations between market power and firm characteristics result from firms' product or labor market power. In this study, we carefully differentiate the two market power types using recent methodological advances building upon Dobbelaere & Mairesse (2013).

[3] For instance, De Loecker & Warzynski (2012) report a positive association between markups and export status in Slovenia, Autor et al. (2020) estimate a positive correlation between markups and firm size for the U.S., De Loecker et al. (2016) find the same for India, and Bellone et al. (2016) report that markups are increasing with firm productivity in France.

Second, and related, we show that the documented negative correlations between firm size and markups turn positive after we condition on wage markdowns.[4] This is because product markups and markdowns are negatively correlated, pointing to interactions between firms' product and labor market power that may shape the markup-size correlation. The extent to which such interactions are relevant for firms is determined by the underlying mode of competition and features of product and labor market institutions. Such market features can vary between countries and can influence whether markups increase or fall with firm size.

Our findings do not necessarily contradict Marshall's second law of demand (i.e., that larger firms face a less elastic demand), which would be the usual explanation for a negative correlation between markups and firm size (e.g., Zhelobodko et al. (2012), Dhingra & Morrow (2019)). As controlling for markdowns restores the positive size-markup correlation, our evidence rather suggests that markups fall with firm size because of interactions between firms' labor and product market power.

Our results provide two important insights for the literature: first, existing models featuring a positive markup-size correlation might draw potentially wrong conclusions on how markup heterogeneity affect economic outcomes. For instance, because the correlations between markups, markdowns, and firm size jointly affect the extent to which large firms over- or underproduce and the type of optimal policies

[4] Markdowns are defined as the marginal revenue product of labor (MRPL) over labor costs per worker. Following the literature, we interpret them as a measure of labor market power. They can be below or above unity, because of, respectively, monopsony power or rent-sharing.

to address distortions (product vs. labor market policies). Second, the negative correlation between product markups and wage markdowns points to interactions between firms' product and labor market power, which have potentially large implications. For instance, we show that if firms share product market rents with workers, rising product markups will not necessarily decrease wages and labor's share as argued in recent work (e.g., De Loecker et al. (2020), Deb et al. (2022)).[5] Our brief study therefore sheds new light on the role of markup heterogeneity in shaping economic outcomes and calls for explicitly considering interactions between labor and product market power in future work.[6]

The remainder proceeds as follows: Section 2 presents the data. Section 3 explains the estimation of markups and markdowns. Section 4 presents results. Section 5 provides further discussion. Section 6 concludes.

2 Data

We use two datasets. One is a detailed firm-product-level panel-dataset on German manufacturing sector firms that is supplied by the statistical offices of Germany (AFiD-Data). The second is a micro-aggregated cross-country dataset that we

[5] The rent-sharing literature already showed that product rents can be passed on to workers if workers have bargaining power (e.g., Van Reenen (1996), Kline et al. (2019)). Mertens (2022) documents that firm- and industry-level labor shares are positively correlated with product markups in the German manufacturing sector.

[6] Recent work studies the role of labor market power, yet, without discussing potential interactions between firms' product and labor market power (e.g., Jha & Rodriguez-Lopez (2021), Macedoni (2021), Berger et al. (2022a, 2022b)).

collected and published together with the CompNet team and several national statistical institutes and central banks in Europe (CompNet data).

2.1 Firm-product German manufacturing sector data: AfiD Data

The first part of the analysis is performed using a rich firm-product-level panel dataset for the German manufacturing sector, which is collected and supplied by the statistical offices of Germany and covers the years 1995-2016.[7] The data contains information on firms' employment, investment, revenue, and, most importantly, product quantities and prices at a ten-digit product classification.[8] Observing firm-specific prices and output quantities allows us to estimate a quantity-based production model of firms and to address the price bias when estimating markups.

To limit administrative burden, the statistical offices collect this data only for firms with at least 20 employees. Furthermore, some variables are only collected for a representative and periodically rotating firm sample, covering 40% of all manufacturing firms with at least 20 employees. We focus on this 40% sample as it contains necessary information for estimating markups. Online Appendix A.1 provides further details on the German data.[9]

[7] Data source: RDC of the Federal Statistical Office and Statistical Offices of the Federal States, DOI: 10.21242/42131.2017.00.03.1.1.0, 10.21242/42221.2018.00.01.1.1.0, and 10.21242/42111.2018.00.01.1.1.0.

[8] The 10-digit product classification defines about 6,000 products. Examples of product categories are: "Workwear – Long trousers for men, cotton", "Tin sheets and tapes, thicker than 0.2mm", "Passenger cars, petrol engine ≤ 1,000 cm³"

[9] We clean the data from top and bottom two percent outliers with respect to revenue over labor, capital, intermediate input expenditures, and labor costs. We 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.

2.2 European cross-country data: CompNet data

The CompNet data contains aggregated firm-level information. The data is collected from harmonized data collection protocols that run over administrative and representative firm-level databases of 19 European national statistical institutes and central banks. These protocols calculate various firm-level performance measures, including firms' markups, labor markdowns, and size, aggregated at the two-digit industry level.

Although the data is aggregated, it contains various moments of the firm distributions (means, percentiles, standard deviations). Most notably, the data provides "joint distributions" which summarize variables by deciles/quintiles of the distributions of other variables (e.g., markups by firm size quintiles). These joint distributions are key for our analysis. The underlying firm population is truncated at a 20 employees cut-off.[10] To ensure representativeness and comparability across countries, variables are weighted by firm population weights.

There are multiple vintages of the data that differ in terms of coverage and variables. We use the 8th vintage CompNet data. It covers the years 1999-2019 and the NACE rev. 2 industries 10-33 (manufacturing), 41-43 (construction), 45-47 (wholesale/retail trade and repair of motor vehicles and motorcycles), 49-53 (transportation/storage), 55-56 (accommodation/food services), 58-63 (ICT), 68 (real

[10] For a smaller set of countries, the data is also available without a size cut-off. An advantage of the truncated data is that it generates more variation along the deciles/quintiles of the firm size distribution. Nevertheless, all results hold for the data without the size cut-off.

estate), 69-75 (professional/scientific/technical activities), and 77-82 (administrative/support service activities).

Table 1 presents the yearly and sectoral coverage of the CompNet data for each country. Yearly coverage varies from 9 to 21 years. The sectoral coverage is, with exception of the real estate sector, the Danish ICT sector, and the early German years, complete and homogenous across countries. Online Appendix A.2 provides more details on data access and sources. For further information on the data, we refer to CompNet's User guide (CompNet (2021)).[11]

[11] Recently, the data has been used, among others, in Berthou et al. (2020), Autor et al. (2020), and Bighelli et al. (2022).

TABLE 1

COMPNET DATA, COVERAGE INFORMATION

Country	Years (1)	Excluded sectors (2)	Median firms' number of employees (4)
Belgium	2000-2018	None	36.42
Croatia	2002-2019	None	39.00
Czech Republic	2005-2019	None	41.40
Denmark	2001-2016	Real estate activities and ICT	36.11
Finland	1999-2019	Real estate activities	38.38
France	2004-2016	None	37.60
Germany*	2001-2018	None	43.22
Hungary	2003-2019	None	38.18
Italy	2006-2018	Real estate activities	35.00
Lithuania	2000-2019	None	38.60
Netherlands	2007-2018	Real estate activities	39.62
Poland	2002-2019	None	44.56
Portugal	2004-2018	None	35.60
Romania	2007-2019	Real estate activities	38.46
Slovakia	2000-2019	None	48.55
Slovenia	2002-2019	None	41.95
Spain	2008-2019	None	34.00
Sweden	2003-2019	None	37.47
Switzerland	2009-2018	None	44.20

Notes: Table 1 reports basic statistics on the CompNet data. Column (1) reports the covered years, column (2) lists the one-digit sectors excluded from the underlying firm-level dataset, and column 3 reports associated averages of the firm-level median number of employees. All statistics refer to firms with at least 20 employees.

* Sectoral coverage varies over time in Germany. For 2005-2018, all sectors are covered.

3 Obtaining markups and markdowns

Markups. We apply the production approach of Hall (1986) and De Loecker & Warzynski (2012) to estimate markups.[12] Assuming that intermediate inputs are flexible and that their prices are exogenous to firms, markups (μ_{it}) can be estimated from the firm's first order condition on intermediate inputs (see online Appendix B.1 for the full derivation):

[12] Subsection 5.1 discusses the main assumptions of this approach and their relevance for our study.

$$\mu_{it} \equiv \frac{P_{it}}{MC_{it}} = \theta_{it}^{M} \frac{P_{it}Q_{it}}{z_{it}M_{it}}. \tag{1}$$

θ_{it}^{M} is the intermediate input output elasticity. MC_{it}, P_{it}, and Q_{it} denote marginal costs, prices, and quantities, respectively. $z_{it}M_{it}$ are intermediate input expenditures.

Markdowns. We follow recent work building upon Dobbelaere & Mairesse (2013) and consider that labor markets can feature firm-side (monopsony) and worker-side (rent-sharing) labor market power (e.g., Caselli et al. (2021), Yeh et al. (2022), Mertens (2022)). As shown in these studies (see also online Appendix B.2), combining the first order condition for labor with equation (1) yields an expression for labor markdowns:

$$\gamma_{it} \equiv \frac{MRP_{it}^{L}}{w_{it}} = \frac{\theta_{it}^{L}}{\theta_{it}^{M}} \frac{z_{it}M_{it}}{w_{it}L_{it}}. \tag{2}$$

θ_{it}^{L} is the output elasticity of labor. MRP_{it}^{L}, w_{it}, and L_{it} denote the marginal revenue product of labor, wages, and labor inputs, respectively.

Recovering output elasticities. To estimate markups and markdowns, we need to recover firms' output elasticities by estimating firms' production functions.

For the German firm-product-level data, we estimate a translog production function using a control function approach as in Wooldridge (2009) and control for firms' input *and* output price variation following De Loecker et al. (2016). From that, we obtain unbiased quantity-based output elasticities. The precise method is explained in online Appendix C.[13]

[13] We follow the literature and rely on a time-constant translog production function (which features firm-specific and time-varying output elasticities). In online Appendix D.2.3, we allow for time-varying production function parameters, which is a parsimonious way of accounting for industry-

The CompNet data directly contains markups derived from industry-specific Cobb-Douglas production functions. As we study the association between markups and firm size *within industries*, any biases in output elasticities will not affect our results. This is because the Cobb-Douglas production function defines constant *industry-specific* output elasticities which are absorbed by industry fixed effects. Hence, price and simultaneity biases are no concern for our results based on the CompNet data. Reassuringly, results are fully consistent with those obtained from the AFiD data using a translog production function and firm-level prices.

4 Results

4.1 German manufacturing sector

We first present results for the German manufacturing sector as this data allows us to estimate state-of-the-art market power measures based on flexible translog production functions that are not subject to simultaneity and price biases.

Online Appendix Table C.1 provides summary statistics for the German data. We estimate markups and markdowns for 242,303 firms. Average markups (markdowns) equal 1.10 (1.00) with a standard deviation of 0.04 (0.26).

specific biased technological change (De Loecker et al. (2020)). Our results are fully robust to this and various other specifications (i.e., different functional forms) and estimation approaches (OLS, Cobb-Douglas cost-shares, different timing assumptions on inputs) that we tested.

Figure 1 shows binned scatter plots that project logged markups on logged firm size and absorb year and 4-digit industry fixed effects.[14] We find a strong negative association between firms' markups and size (Panel A), which turns positive after conditioning on markdowns (Panel B). This results from a negative correlation between firms' product and labor market power (Panel C).[15]

[14] We focus on log-log relationships to minimize the effect of measurement error in the markup estimation. As markups are bounded by zero and binned scatter plots average markups by quantiles of sales, measurement errors may artificially increase average markups. If measurement noise is larger for small firms, this could artificially generate the negative relationship with firm size. The log-transformation prevents this.

[15] Online Appendix D.2.4 shows that markdowns are positively correlated with firm size.

MARKUPS AND FIRM SIZE, GERMAN MANUFACTURING SECTOR

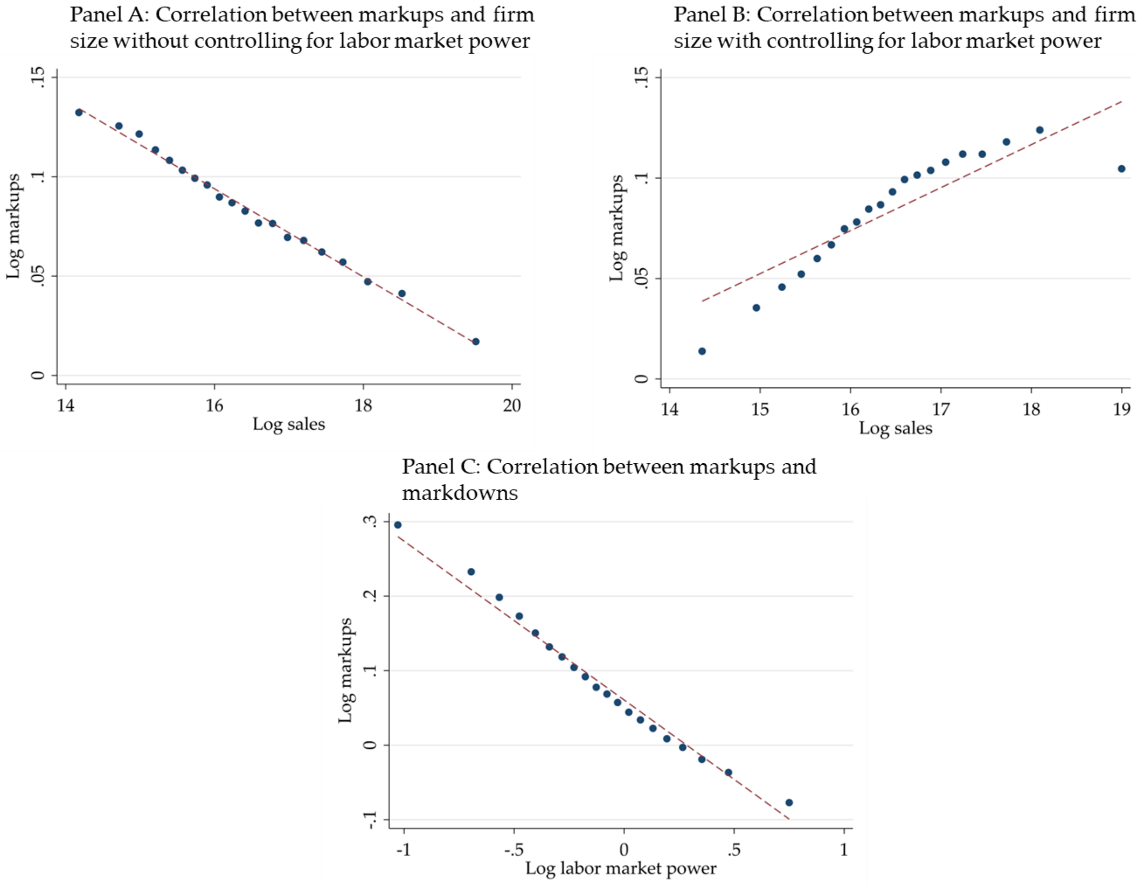


FIGURE 1 – Binned scatter plots from firm-level regressions of log markups on log firm size and log labor markdowns while controlling for year and four-digit industry fixed effects. Panel A (B) shows results from projecting markups on firm size without (with) controlling for firms' markdowns. Panel C shows results from regressing markups on markdowns. German manufacturing sector data. 1995-2016. 242,303 firm-year observations.

Table 2 presents associated regression results from projecting markups on firm size while controlling for industry and year fixed effects. The results are in line with Figure 1 (columns 1-2) and hold when defining firm size in terms of employment (columns 3-4). In columns 5-8, we go even one step further and reduce the sample to single-product firms and control for detailed 10-digit product-fixed effects using data on firms' manufactured products. This controls for differences in firms' output that cannot be captured by industry fixed effects. Even from this restrictive specification that compares only single-product firms manufacturing the same 10-digit product, we document a negative association between firms' markups and size that only turns positive after conditioning on markdowns.[16]

TABLE 2

MARKUPS AND FIRM SIZE

	Log Markups							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log sales	-0.022***	0.021***			-0.020***	0.032***		
	(0.001)	(0.001)			(0.001)	(0.001)		
Log employment			-0.024***	0.022***			-0.022***	0.035***
			(0.001)	(0.001)			(0.002)	(0.001)
Log markdowns		-0.250***		-0.241***		-0.260***		-0.251***
		(0.003)		(0.002)		(0.004)		(0.004)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Product FE	No	No	No	No	Yes	Yes	Yes	Yes
Single product firms	No	No	No	No	Yes	Yes	Yes	Yes
Observations	242,303	242,303	242,303	242,303	82,942	82,942	82,942	82,942
R-squared	0.148	0.450	0.140	0.445	0.339	0.565	0.337	0.560
Num. firms	44,600	44,600	44,600	44,600	17,855	17,855	17,855	17,855

Notes: Table 2 reports results from projecting firm markups on firm size (sales). Columns 1-4 show results for the full sample. Columns 5-8 show results for the single-product firm sample. German manufacturing sector data. 1995-2016. Standard errors are reported in parentheses and clustered at the firm level. Significance: *10 percent, **5 percent, ***1 percent.

4.2 European evidence

To describe how markups vary across the firm size distribution in Europe, we use the CompNet data's "joint distributions". These joint distributions report median markups, sales, and markdowns for each quintile of the firm sales distribution within each two-digit industry and year. Using these joint distributions, we regress markups on firm size at the industry-year-size-quintile level:

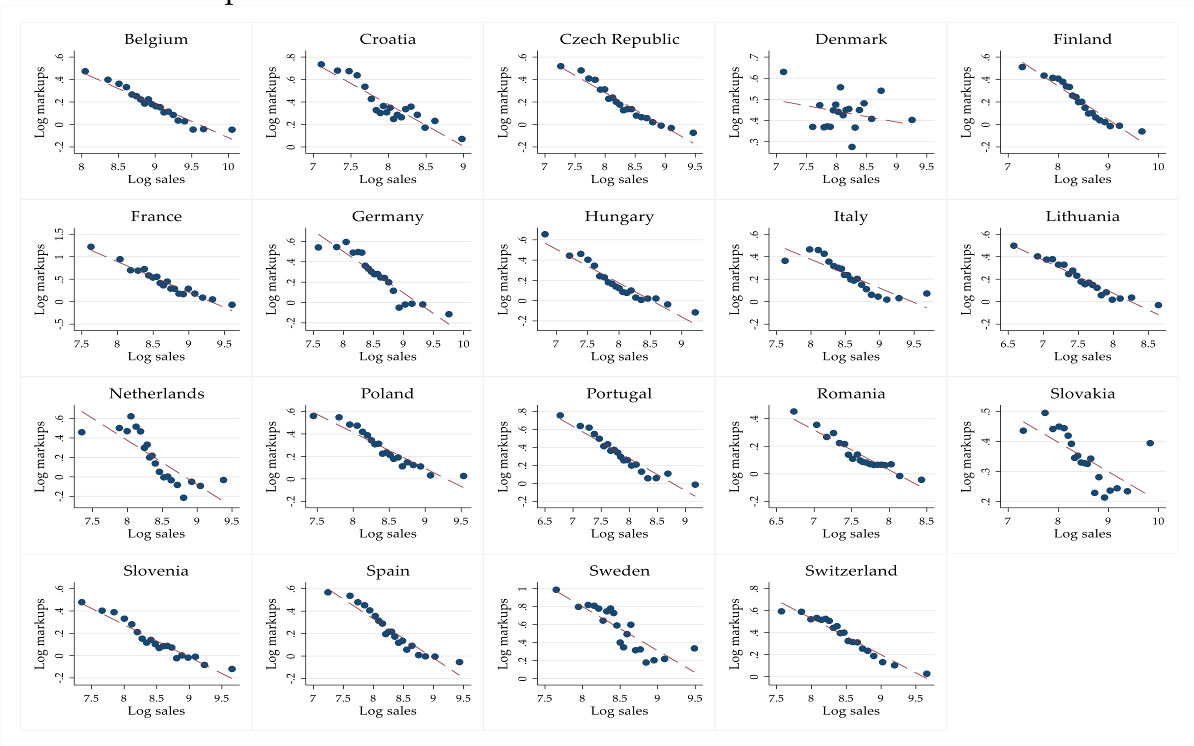
$$\bar{\mu}_{kjt} = log(\overline{P_{\iota t} Q_{\iota t}})_{kjt} + \vartheta_j + \vartheta_t + \varepsilon_{kjt}. \quad (3)$$

[16] Online Appendix D.2.1 reproduces results using market shares as a size measure. Results are fully robust.

$\bar{\mu}_{kjt}$ and $log(\overline{P_{\iota t}Q_{\iota t}})_{kjt}$ are the logs of, respectively, median markups and median sales in quintile k of the sales distribution in two-digit industry j and year t. ϑ_j and ϑ_t capture industry and year fixed effects. We estimate this regression separately by country.

Figure 2 shows binned scatter plots from regression (3). Panel A shows a consistent unconditional negative association between markups and firm size for every country. Panel B reports the same plots after controlling for firms' markdowns. Consistent with the results from the rich German manufacturing sector data, all correlations between markups and firm size turn positive after conditioning on markdowns. Hence, labor market power is key in shaping how markups relate to firm size.

Panel A: Markups and firm size



Panel B: Markups and firm size controlling for labor markdowns

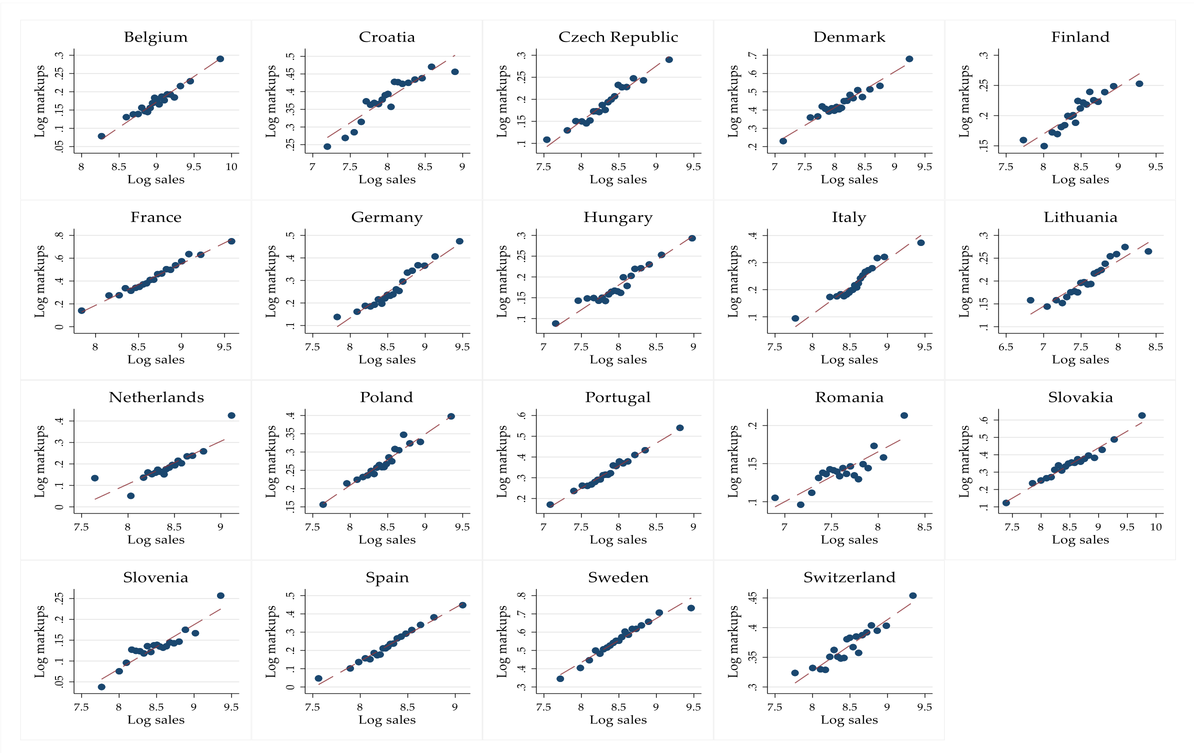


FIGURE 2 – Binned scatter plots from quintile-level regressions of median markups on median firm size along quintiles of the sales distributions within two-digit industries (all in logs). Panel A (B) reports results without (with) controlling for median log markdowns. All regressions control for year and industry fixed effects. CompNet data 1999-2018. Yearly and sectoral coverage varies by country as described in Table 2.

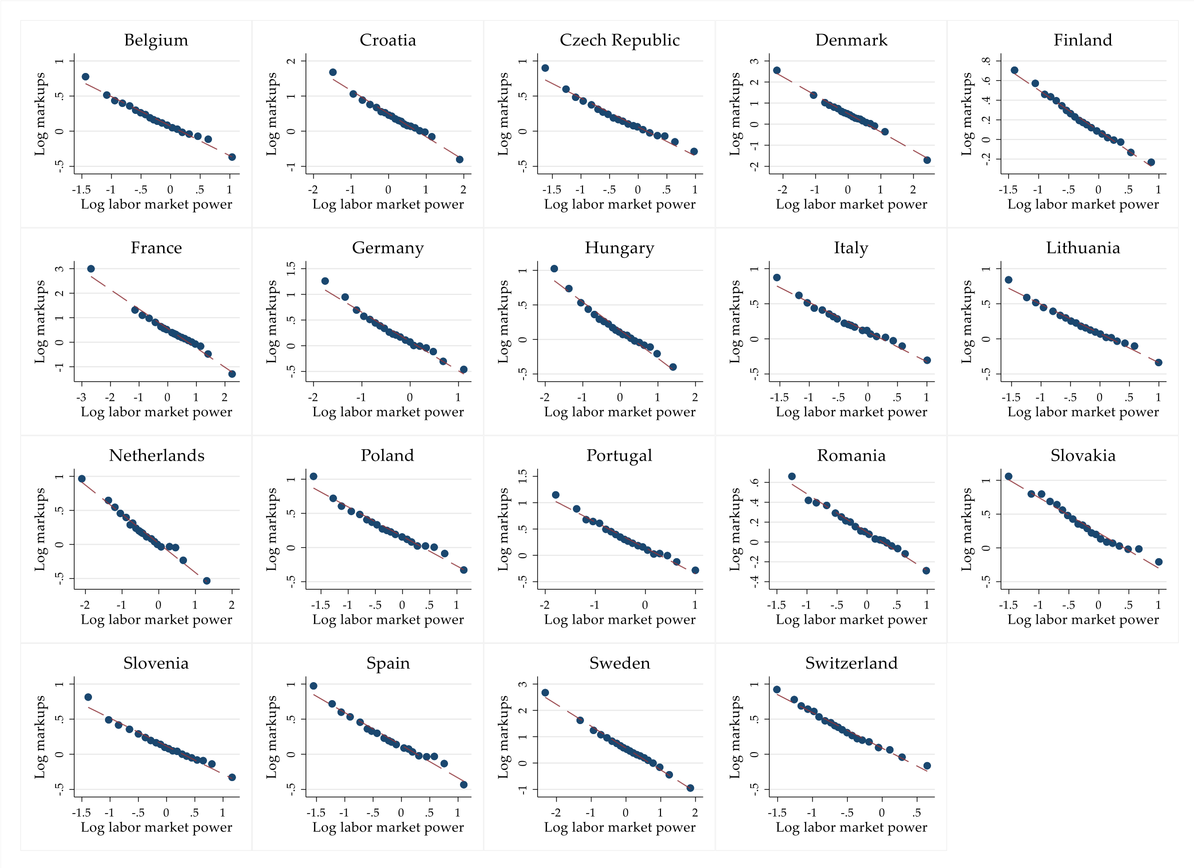


FIGURE 3 – Binned scatter plots from firm-level regressions of logged median markups on logged median markdowns along quintiles of the sales distributions within two-digit industries (see regression equation (3)). All regressions control for year and industry fixed effects. CompNet data 1999-2018. Yearly and sectoral coverage varies by country as described in online Appendix A.2.

Finally, Figure 3 shows results from projecting markups on markdowns. In line with the German micro data, markdowns and markups are negatively associated in all countries.

Our findings show that the negative association between markups and firm size is a robust feature of the European data. Despite larger firms are typically expected to face a less elastic demand (Marshall's second law of demand), they charge lower markups. This has important implication for a wide range of economic topics which we discuss in section 5.3.

As controlling for markdowns restores the positive correlation between firm size and markups, interactions between firms product and labor market power, which are not captured by standard models, offer an appealing explanation for our findings. Depending on the underlying institutions and mode of competition, such interactions might incentivize firms to employ different strategies to become profitable. For instance, either by generating high markups and sharing rents with their workers, or by exploiting their workers and being highly competitive in their product markets through which firms can scale up their size. Deriving a full model featuring such market power interactions is beyond the scope of this study. Nevertheless, online Appendix B.2.4 provides a simple sketch of a rent-sharing model in which worker power falls with firm size.[17] In such a model, large firms have an incentive to keep markups low in order to expand market shares and to extract additional rents from labor markets (i.e., to share fewer rents with workers).

5 Discussion

5.1 Robustness of our approach

The production approach to markup estimation has recently received large attention in the literature. This subsection discusses the main criticism of this method and how it could affect our results.

[17] This is supported by empirical evidence. Using the same German data, Mertens et al. (2022) show that larger firms have lower rent-sharing elasticities.

Mismeasurement of output elasticities. One of the main criticisms of the production approach arises from unobserved firm-level prices, causing biased estimates of output elasticities (Bond et al. (2021)). This concern does not apply to our study, because our German data allows distinguishing prices and quantities, while our European analysis does not require any production function estimation results. This is because, due to the Cobb-Douglas structure, output elasticities are constant across firms within industries. In this case, within-industry markup variation is fully driven by variation in input expenditure shares, leaving no room for biases in output elasticities to affect our results.

To further underline that the markup-size correlation in the German data is not an artefact of specificities of the production function estimation, online Appendix D.2.6 additionally shows that using pure input shares reproduces the negative size-markup correlation.[18]

Monopsony power in intermediates. Our approach to markup estimation requires a flexible input for which input prices are exogenous to firms. Following the literature, we rely on intermediate inputs. If firms held monopsony power in this market though, the right-hand side of equation (1) would be multiplied by the wedge $\gamma_{it}^{M} \equiv \frac{MRP_{it}^{M}}{z_{it}}$, where MRP_{it}^{M} is the marginal revenue product of intermediates. This wedge captures a firm's market power over its intermediate input suppliers. Our

[18] Specifically, sales over intermediate expenditures are negatively correlated with firm size. We also show that, consistently with Autor et al. (2020), labor shares are negatively correlated with firm size which is driven by a positive correlation between markdowns and firm size (see also online Appendix D.2.4).

markups and markdowns (equations (1) and (2)) would then have, respectively, an upward and a downward bias growing in γ_{it}^{M}.

Yet, we are not concerned that this type of measurement error can explain our findings. Note that we are not interested in markup levels. Rather, we study the correlation between markups and firm size. To explain the negative markup-size correlation, intermediate input monopsony power would need to be higher in small firm than in large firms. Yet, the literature established the opposite (e.g., Morlacco (2020)). We therefore conclude that unobserved monopsony power in intermediate input markets is unlikely to explain our results.

Adjustment costs in intermediates. Bond et al. (2021) highlight that another identification issue may arise if the flexible input chosen for the markup estimation is subject to adjustment costs. However, this does not apply to our case, as we do not use a generic variable input bundle. Instead, we rely on intermediate inputs as a flexible variable, which are typically not considered subject to adjustment costs in the literature (e.g., Hall (2004)).

Additionally, unobserved adjustments costs in intermediates would actually strengthen our results as they artificially create a *positive* association between firm size and markups (Gamber (2022)). This can be seen from the markup formula (1). For a given output elasticity, changes in sales that do not correspond to an adjustment in intermediate input expenditures will create an artificial positive association between sales (i.e., size) and the markup.

Inputs that influence product demand. Finally, Bond et al. (2021) emphasize that markups will be also biased if the flexible input (intermediates) is used to influence product demand (e.g., marketing expenditures). Because we rely on intermediates to estimate markups, which mostly consist of raw materials, renting expenditures, and goods for resale, we do not believe that this is a large concern for our results. Nevertheless, to further scrutinize this concern, online Appendix D.2.2 (Table D.3), reports our regressions projecting markups on firm size for several subgroups of firms. We split firms based on their industry-classification into firms mainly producing i) consumer goods, ii) intermediate goods, and iii) investment goods.[19] Arguably, marketing expenditures are much more relevant for consumer than for investment good producers. Additionally, we also split firms into exporter and non-exporter as exporting might involve additional overhead costs or marketing expenditures due to operating in multiple locations. As we do not find any notable differences between any of these firm types, we argue that our results are not explained by incorrectly accounting for product-demand-related intermediate input expenditures.

[19] We classify industries according to the Commission Regulation (EC) No 656/2007. This classification assigns industries to consumer, investment, and intermediate goods based on their main production activities.

5.2 Comparison with other studies

Our findings seem to contradict several existing studies reporting a positive cross-sectional correlation between markups and firm size, most notably, recent work by Autor et al. (2020) and De Loecker et al. (2020). Yet, a few studies also find that markups are lower in larger firms (Caselli et al. (2018), Diez et al. (2021)). Additionally, several studies document positive correlations between markups and firm size after conditioning on firm fixed effects, which effectively relates *changes* in markups to *changes* in firm size (e.g., De Ridder et al. (2022)).[20] The latter is fundamentally different from the cross-sectional correlation highlighted in theoretical work and absorbs firm-specific factors related to labor market power.

How can we explain these findings in the literature? First, interactions between product and labor market power and their impact on the markup-size correlation are determined by the underlying mode of competition and institutions. Variations in these factors across countries and industries might explain part of the differences between other studies and our findings.

However, our robust evidence for a negative association between markups and firm size across 19 European countries suggests that different approaches to measuring markups might be more relevant. Recap that the markup is the wedge between the flexible input's output elasticity and that input's inverse expenditure

[20] Additionally, Burstein et al. (2020) report a negative correlation between markups and market shares in specifications either without industry fixed or with firm fixed effects. The latter, again, effectively compares changes, whereas the former does not account for heterogeneity between industries.

share in sales (equation (1)). A key condition for estimating markups is that firms do not have market power in the flexible input's market. Hence, the methodology of estimating markups of De Loecker & Warzynski (2012) requires researchers to take a stance on which input is best suited for estimating markups. Depending on data constraints and other factors, studies depart in the choice of that input.

Consider the case in which firms have labor market power, but intermediate input prices are exogenous. Deriving markups from firms' labor input decision yields a measure combining product and labor market power:

$$\mu_{it}^{L} = \mu_{it}\gamma_{it} = \theta_{it}^{L}\frac{P_{it}Q_{it}}{w_{it}L_{it}}, \tag{4}$$

where μ_{it}^{L} deviates from the true markup, μ_{it}. μ_{it}^{L} is the markup estimator originally proposed by De Loecker & Warzynski (2012) and used, among others, by Autor et al. (2020). In the presence of labor market power, this expression reflects a meaningful measure of firms' overall market power on labor and output markets. Yet, results based on μ_{it}^{L} do not necessarily reflect a positive correlation between firm size and markups (μ_{it}) but could equally capture a positive correlation between labor markdowns (γ_{it}) and firm size. In fact, online Appendix D.2.5, Table D.5 shows that markups as computed in equation (4) *increase* with firm size, which results from a positive correlation between wage markdowns (γ_{it}) and firm size (Appendix D.2.4). Given widespread evidence on firm- and worker-side labor market power, relying on equation (4) to estimate markups might be problematic.[21]

[21] See, for instance, Card et al. (2018), Mertens (2020, 2022), Brooks et al. (2021), Manning (2021).

Similarly, De Loecker et al. (2020) and De Loecker & Eeckhout (2020) use a markup expression based on combining labor and intermediates into one joint input. Assuming that intermediates are flexible and that intermediate input prices are exogenous to firms, their markup expression (μ_{it}^{DLEU}) is a weighted average of markups and markdowns: $\mu_{it}^{DLEU} = ((\theta_{it}^{M} + \theta_{it}^{L})/(\theta_{it}^{M}\gamma_{it} + \theta_{it}^{L}))\mu_{it}\gamma_{it}$ (see Mertens (2022)). Again, any positive association between μ_{it}^{DLEU} and firm size can reflect a positive association between labor markdowns and firm size (see online Appendix D.2.5).

5.3 Implications

Throughout all 19 countries of this study, we find that markups are smaller in larger firms, whereas markups and markdowns are negatively correlated. What are the implications of these findings?

Misallocation. Markups create wedges in firms' first order conditions and dispersion in these wedges across firms implies a production factor misallocation – economic output could be increased by moving inputs from firms with small to firms with large wedges (Hsieh & Klenow (2009)).[22] A large literature attempts to quantify the economic losses from misallocation based on theories that model a positive markup-size correlation. If the correlation between markups and firm size is positive, markups cause large firms to underproduce. Consequently, size-dependent taxes (or

[22] If wedges decline with increasing input usage (decreasing marginal products).

antitrust policies) will reduce the aggregate markup but increase markup-induced misallocation in the economy (Edmond et al. (2022)). If markups are negatively correlated with firm size, as we document, size-dependent taxes can reduce misallocation from markup dispersion, reversing the impact of the policy. As discussed below, input wedges, however, also distort the firm size distribution. Hence, even if markups fall with firm size, large firms might underproduce if input wedges are positively correlated with firms' size.

International trade. Similarly, the gains from trade in models with heterogenous markups change, if markups decrease with firm size because the extent to which trade can reduce markup-induced misallocation is defined by the joint distribution between firm size and markups (Edmond et al. (2015)). Intuitively, if the largest (most productive) producers do not have the largest markups, there is only small room for product market competition to reduce markups of large firms. Consequently the correlation between firm size and markups is key for determining optimal policies in the economy.

Product vs. input market policies. Similar to markups, labor markdowns create wedges in firms' first order conditions. The extent to which product and labor market power offset or strengthen each other is an empirical question. We document a negative correlation between both.[23] This implies that size distortions from product and labor market power partially offset each other.

[23] For instance, Tortarolo & Zarate (2020) document a positive correlation between markups and markdowns for the U.S. Yet, their markdown measure cannot capture rent-sharing.

The overall distortion from labor and product market power is a weighted average of distortions coming from both market power types. Hence, despite a negative markup-size correlation, wedges can still grow with firm size if labor market power is sufficiently positively correlated with firm size.[24] In that case, large firms still underproduce, as suggested by the literature, but for a different reason. Understanding how input and product market power relate to firm size (and productivity) and to each other is key for designing optimal policies because policies addressing both market power types differ. Whereas product competition policies predominantly affect markups, minimum wages or a strengthening of labor market institutions (unions, work councils, etc.) directly affect firms' labor market power. These policies thus create different effects on overall distortions and misallocation.

Pass-through and rent-sharing. The pass-through of shocks from firms to consumers and workers (input suppliers), depends on firms' relative market power in product and labor (input) markets. For instance, the pass-through from cost-shocks to consumer prices is affected by the demand elasticity and the markups that firms charge (De Loecker et al. (2016)). Similarly, cost shocks will be passed through to workers in form of lower/higher wage growth, depending on firms' labor market power. For instance, product market competition shocks will reduce worker rents if there is rent-sharing. This is highly relevant in context of recent work emphasizing the potential negative effects of rising markups on wages and labor shares (e.g., De

[24] Online Appendix D.2.4 reports a positive correlation between firm size and markdowns.

Loecker & Eeckhout (2020), Deb et al. (2022)). Specifically, if firms share gains from product markups with their workers, labor market effects from rising markups are ambiguous and differ compared to situations without rent-sharing. In this case, higher markups may even increase wages and the negative labor market effects from rising markups on wages and labor shares discussed in the literature will be weakened or even reversed. Online Appendix B.2.3 illustrates this further and shows that in a standard rent-sharing model, firms' labor share will *increase* in response to an increase in markups, if rent-sharing is sufficiently strong.[25]

6 Conclusion

This short study documents a robust negative cross-sectional correlation between markups and firm size and reveals evidence of important interactions between firms' product and labor market power. Our findings hold in rich German manufacturing sector firm-level data and in micro-aggregated data across a large set of European countries and sectors. Our methodology is robust to common criticism on markup estimation.

We discuss the implications of our findings and highlight that studying product and labor market power and their interactions in an integrated framework is key for future work as, among others, both market power types jointly characterize

[25] Specifically, a firm's labor share increases in response to an increase in the firm's markup if $\phi_{it}/(1-\phi_{it}) > \theta_{it}^{L}/\sum_n \theta_{it}^{n}$, where ϕ_{it} denotes workers' bargaining power and θ_{it}^{L} is the output elasticity of labor. $\sum_n \theta_{it}^{n}$ is the sum of output elasticities of other inputs that enter the profit function in the bargaining model.

misallocation, gains from trade, optimal policy, and the pass-through from firm shocks to consumers and workers.

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Online Appendix – not for print

Appendix A: Details on the Data

Appendix A.1: German manufacturing sector data

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 we used are: "AFiD-Modul Produkte", "AFiD-Panel Industriebetriebe", and "AFiD-Panel Industrieunternehmen".

Variable definitions

The following list presents an overview on the variable definitions for all variables used in this article (includes online Appendix).

- L_{it}: Labor in headcounts (end of September value).
- 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 as described in Mertens (2020, 2022a), 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 below).[26]
- π_{it}: Firm-specific Törnqvist price index, derived as in Eslava et al. (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.

[26] We 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.

- G_{it}: Headquarter location of the firm. 90% of firms in our German data are single-plant firms.
- D_{it}: A four-digit industry indicator variable. The industry of each firm is defined as the industry in which the firm generates most of its sales.
- E_{it} $(or\ in\ logs, e_{it})$: Deflated expenditures for raw materials. 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.

Data preparation

During our 22 years of data, the NACE classification of industry sectors (and thus firms into industries) changed twice. Because our estimation of markups relies on a time-consistent industry classification at the firm level (as we allow for sector-specific production functions and as we use sector-specific deflators), we require a time-consistent 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, we follow Mertens (2022a) and use information on firms' product mix to classify firms into NACE rev 1.1 sectors based on their main production activities. For details, we refer to Mertens (2022a).

Appendix A.2: The CompNet data

Data access and further documentation

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. Further documentation on the data can be found in CompNet's 8th vintage User guide: https://www.comp-net.org/data/8th-vintage/

Underlying data sources

Table A.1 lists the data sources underlying CompNet. These are administrative databases that are collected by national statistical institutes and central banks. The datasets are some of the most representative and comprehensive datasets for the countries covered in CompNet.

TABLE A.1

COMPNET COUNTRY-SPECIFIC DATA SOURCES

Country	Data source	Institute responsible for data	Data provider
Belgium	microBACH (Bank for Accounts of Companies Harmonized)	ECCBSO (European Committee of Central Balance Sheet Data Offices)	European Central Bank
Croatia	Business register, court register	Financial Agency Croatia	Croatian National Bank
Czech Republic	P5-01 survey, business register, foreign trade dataset	Czech Statistical Office	Czech National Bank
Denmark	Account statistics, general enterprise statistics	Statistics Denmark	Central Bank of Denmark
Finland	Structural business and financial statement statistics, international trade statistics data,	Statistics Finland	Statistics Finland
France	Regime of normal real profits, Simplified regime for self-employed	Statistics France (INSEE)	Statistics France (INSEE)
Germany	Official German firm data, annual report on wholesale/retail trade firms, annual report on construction firms, annual report	Destatis	Destatis

	on accommodation and food service firms		
Hungary	Tax registry database of national tax and customs administration, business register, export-import data of Hungarian enterprises	Statistics of Hungary, Central Bank of Hungary, National Tax and Customs Administration	Central Bank of Hungary
Italy	microBACH (Bank for Accounts of Companies Harmonized)	ECCBSO (European Committee of Central Balance Sheet Data Offices)	European Central Bank
Lithuania	Statistics survey on the business structure, business register, customs declarations	Statistics Lithuania, Centre of Registers, Customs of the Republic of Lithuania	Central Bank of Lithuania
Netherlands	Business register, statistics finances of non-financial enterprises	Statistics Netherlands	Statistics Netherlands
Poland	Statistics financial report, various report	Statistics Poland	Central Bank of Poland
Portugal	Integrated business account system	Statistics Portugal	GEE- Ministry of Economy Portugal
Romania	Balance sheet information on non-financial enterprises, exports and imports of goods database	Ministry of Public Finances, Statistics Romania	National Central Bank of Romania
Slovakia	Annual report on production industries, statistical register of organizations, foreign trade statistics	Statistics Slovakia	Central Bank of Slovakia
Slovenia	Agency of the republic of Slovenia for public legal records and related services	Institute of Macroeconomic Analysis and Development of the republic of Slovenia	Institute of Macroeconomic Analysis and Development of the republic of Slovenia
Spain	microBACH (Bank for Accounts of Companies Harmonized)	ECCBSO (European Committee of Central Balance Sheet Data Offices)	European Central Bank
Sweden	Business register, structured business register	Statistics Sweden	Statistics Sweden
Switzerland	Structural business statistics	Swiss Federal Statistical Office	Swiss Federal Statistical Office

Notes: Table A.1 shows the country specific data sources of the firm data underlying CompNet, the institutions collecting these data, and the data providing institutions in each country.

Appendix B: Deriving Markups and Markdowns

Appendix B.1: Markups

We derive our markup estimator following the production approach of Hall (1986) and De Loecker & Warzynski (2012). Firm i in period t minimizes a variable cost function $C_{it} = w_{it}L_{it} + z_{it}M_{it} + r_{it}K_{it}$, subject to a constraint on the minimum level of output, produced using a continuous and twice differentiable production function $Q_{it} = Q_{it}(L_{it}, K_{it}, M_{it}, e^{\omega_{it}})$. L_{it}, M_{it}, and K_{it} denote labor, intermediates, and capital inputs, respectively, while w_{it}, z_{it}, and r_{it} are the associated unit input costs. Assuming that intermediate inputs are flexible and that their prices are exogenous to firms, the cost minimization problem yields the following FOC with respect to intermediate inputs:

$$z_{it} = \lambda_{it} \frac{\partial Q_{it}}{\partial M_{it}}, \tag{B.1}$$

where λ_{it} is the Lagrange multiplier and, in this setting, corresponds to the marginal cost.

Our markup estimator (equation (1) in the main text) is obtained by combining condition (B.1) with the definition of the markup, $\mu_{it} = \frac{P_{it}}{\lambda_{it}}$, and the output elasticity, $\theta_{it}^{X} = \frac{\partial Q_{it}}{\partial X_{it}} \frac{X_{it}}{Q_{it}}$, where $X = \{L, M, K\}$:

$$\mu_{it} = \theta_{it}^{M} \frac{P_{it}Q_{it}}{z_{it}M_{it}}. \tag{B.2}$$

Appendix B.2: Markdowns

We follow recent work extending the production approach to derive an expression for markdowns. Some studies focus on monopsony power (e.g., Yeh et al. (2022)), whereas other work additionally allows for rent-sharing and worker bargaining power (e.g., Dobbelaere & Mairesse (2013), Mertens (2022a)). We first present a monopsony model in Appendix B.2.1 and subsequently discuss a model with rent-sharing in Appendix B.2.2. Both models yield the same markdown estimator.

Appendix B.2.1: Monopsony model

In standard monopsony models, labor is chosen in a static profit maximization problem without strategic interactions.[27] Wages may vary with employment, as the firm-specific labor supply can be upward-sloping:

(B.3) $$Max_{L_{it}}\ P_{it}Q_{it} - w_{it}L_{it} - z_{it}M_{it} - r_{it}K_{it}.$$

Rearranging the optimality condition, $MRP_{it}^{L} = \frac{\partial w_{it}}{\partial L_{it}} L_{it} + w_{it}$, one can express the markdown ($\gamma_{it} = \frac{MRP_{it}^{L}}{w_{it}}$) in terms of the slope of labor supply.

(B.4) $$\gamma_{it} = 1 + \frac{\partial w_{it}}{\partial L_{it}} \frac{L_{it}}{w_{it}}$$

Firm's optimal behavior is still consistent with the cost minimization problem in Appendix B.1. However, the left-hand side of the FOC with respect to labor does not

[27] These assumptions are not required to derive the markup estimator, as cost minimization is consistent with different profit strategies and dynamic optimization problems.

perfectly mirror equation (B.1), because, unlike the price of intermediate inputs, wages are not exogenous to the firm's decision:

$$\frac{\partial w_{it}}{\partial L_{it}} L_{it} + w_{it} = \lambda_{it} \frac{\partial Q_{it}}{\partial L_{it}}. \tag{B.5}$$

Our markdown estimator (equation 2 in the main text) is obtained by first combining equations (B.4) and (B.5) with the definition of the output elasticity and then substituting λ_{it} with the firm's price and the markup estimator from equation (B.2).[28] Formally:

$$\gamma_{it} = 1 + \frac{\partial w_{it}}{\partial L_{it}} \frac{L_{it}}{w_{it}} = \frac{\theta_{it}^{L}}{\theta_{it}^{M}} \frac{z_{it} M_{it}}{w_{it} L_{it}}. \tag{B.6}$$

Appendix B.2.2: Bargaining model

We follow standard bargaining models (e.g., McDonald & Solow (1981), Van Reenen (1996), Crepon (2005)), and assume that profit-maximizing firms bargain with risk-neutral workers over wages (w_{it}) and employment (L_{it}). Employees maximize their utility function, given by:

$$U(w_{it}, L_{it}) = w_{it} L_{it} + (\bar{L}_{it} - L_{it}) \bar{w}_{it}. \tag{B.7}$$

$\bar{w}_{it} \leq w_{it}$ is the reservation wage. $\bar{L}_{it}$ is the competitive employment level.

Firms produce output using the production function $Q_{it} = Q_{it}(L_{it}, K_{it}, M_{it}, e^{\omega_{it}})$. In the event of a breakdown of negotiations, workers receive the reservation wage,

[28] The markup estimator can also be derived by taking the FOC with respect to intermediates from (B.3).

whereas the firm's outside option is to not produce at all. Formally, workers and their firm solve the following Nash-bargaining problem:

$$\max_{w_{it},\, L_{it},\, M_{it}, K_{it}} [\phi_{it} \log(L_{it}(w_{it} - \overline{w}_{it}) + (1 - \phi_{it}) \log(P_{it}Q_{it} - w_{it}L_{it} - z_{it}M_{it} - r_{it}K_{it})], \tag{B.8}$$

where $\phi_{it} \in [0,1]$ denotes workers' bargaining power. The first order condition with respect to L_{it} implies:

$$w_{it}\left(1 - \frac{\phi_{it}}{1 - \phi_{it}} \frac{\Pi_{it}}{w_{it}L_{it}}\right) = MRP_{it}^{L}, \tag{B.9}$$

where Π_{it} denotes profits. Hence, wages exceed the marginal revenue product of labor in this model.

Taking the first order condition with respect to output quantity, one can show that firms set markups consistent with the markup rule in this framework.[29] This ensures us that $MRP_{it}^{L} = \frac{P_{it}}{\mu_{it}} \frac{\partial Q_{it}}{\partial L_{it}}$[30]. Combining the latter with the markup expression (B.2) and the definition of the markdown yields the same estimator as in equation (B.6) and equation (2) of the main text:

$$\gamma_{it} = \left(1 - \frac{\phi_{it}}{1 - \phi_{it}} \frac{\Pi_{it}}{w_{it}L_{it}}\right) = \frac{\theta_{it}^{L}}{\theta_{it}^{M}} \frac{z_{it}M_{it}}{w_{it}L_{it}}. \tag{B.10}$$

Markdowns in the bargaining model have the same estimator as in the monopsony model, but the interpretation differs. Under monopsony, γ_{it} reflects the extent to which the labor supply elasticity allows firms to drive wages below competitive

[29] I.e., $\mu_{it} = \frac{1}{1 + \frac{\delta P_{it} Q_{it}}{\delta Q_{it} P_{it}}}$.

[30] $MRP_{it}^{L} \equiv \frac{\delta P_{it} Q_{it}}{\delta L_{it}} = \frac{\delta P_{it}}{\delta Q_{it}} \frac{\delta Q_{it}}{\delta L_{it}} Q_{it} + P_{it} \frac{\delta Q_{it}}{\delta L_{it}} = \left(\frac{\delta P_{it}}{\delta Q_{it}} Q_{it} + P_{it}\right) \frac{\delta Q_{it}}{\delta L_{it}} = \frac{P_{it}}{\mu_{it}} \frac{\partial Q_{it}}{\partial L_{it}}$.

levels, whereas under bargaining, γ_{it} reflects the extent to which worker power can drive wages above competitive levels. Together, both equations provide intuitive explanations for why researchers observe $\gamma_{it} > 1$ and $\gamma_{it} < 1$ in the data. In some studies, these two frictions are used together to jointly motivate firm- and worker-side labor market power (e.g., Dobbelaere & Mairesse (2013), Caselli et al. (2021), Mertens (2022a)). We follow this interpretation.[31]

Appendix B.2.3: Labor shares, markups, and rent-sharing

The bargaining model from Appendix B.2.2 implies that an increase in firm markups does not necessarily lower firm-level labor shares if rents are largely redistributed to workers. Note that the FOC for labor yields:

$$LS_{it} = \frac{w_{it}L_{it}}{P_{it}Q_{it}} = \frac{\theta_{it}^{L}}{\mu_{it}\gamma_{it}}, \tag{B.11}$$

Now, express equation (B.10) as

$$\gamma_{it} = 1 - \frac{\phi_{it}}{1-\phi_{it}}\left(\frac{P_{it}Q_{it}}{w_{it}L_{it}} - 1 - \frac{z_{it}M_{it}}{w_{it}L_{it}} - \frac{r_{it}K_{it}}{w_{it}L_{it}}\right)$$

$$\gamma_{it} = 1 - \frac{\phi_{it}}{1-\phi_{it}}\left(\frac{\mu_{it}\gamma_{it}}{\theta_{it}^{L}} - 1 - \gamma_{it}\frac{\theta_{it}^{M}}{\theta_{it}^{L}} - \gamma_{it}\frac{\theta_{it}^{K}}{\theta_{it}^{L}}\right),$$

$$\gamma_{it} = \frac{1}{(1-\phi_{it})} - \frac{\phi_{it}}{(1-\phi_{it})}\gamma_{it}\left(\frac{\mu_{it} - \theta_{it}^{M} - \theta_{it}^{K}}{\theta_{it}^{L}}\right), \tag{B.12}$$

[31] Note that the above bargaining model is a static framework. This follows the standard rent-sharing literature (see Card et al. (2018) for a review). Strictly speaking, and as highlighted in Mertens (2020, 2022) and Garin & Silverio (2022), rent-sharing requires the existence of firm-side adjustment frictions (e.g., an organized community of workers, sunk training costs). Otherwise, workers have no leverage for bargaining with firms over rents.

where we used the definition of the output elasticity, $\theta_{it}^{X} = \frac{\partial Q_{it}}{\partial X_{it}} \frac{X_{it}}{Q_{it}}$, with $X = \{L, M, K\}$ and the FOC for intermediates and capital, which define $MRP_{it}^{M} = z_{it}$ and $MRP_{it}^{K} = r_{it}$, respectively.

Inserting (B.12) into (B.11) and rearranging, yields:

$$\text{(B.13)} \quad LS_{it} = \frac{\theta_{it}^{L}}{\mu_{it}} \left(1 - \phi_{it} + \phi_{it} \left(\frac{\mu_{it} - \theta_{it}^{M} - \theta_{it}^{K}}{\theta_{it}^{L}} \right) \right) = \phi_{it} + \frac{\theta_{it}^{L} - \phi_{it}\theta_{it}^{L} - \phi_{it}\theta_{it}^{M} - \phi_{it}\theta_{it}^{K}}{\mu_{it}}.$$

The derivative $\frac{\partial LS_{it}}{\partial \mu_{it}}$ is given by:

$$\frac{\partial LS_{it}}{\partial \mu_{it}} = -\underbrace{\frac{\theta_{it}^{L}}{\mu_{it}^{2}}}_{<0} + \underbrace{\frac{\phi_{it}\theta_{it}^{L}}{\mu_{it}^{2}}}_{>0} + \underbrace{\frac{\phi_{it}\theta_{it}^{M}}{\mu_{it}^{2}}}_{>0} + \underbrace{\frac{\phi_{it}\theta_{it}^{K}}{\mu_{it}^{2}}}_{>0},$$

which is positive if:

$$\frac{\partial LS_{it}}{\partial \mu_{it}} > 0 \; if \, \phi_{it}\theta_{it}^{L} + \phi_{it}\theta_{it}^{M} + \phi_{it}\theta_{it}^{K} > \theta_{it}^{L}$$

$$\text{(B.14)} \qquad \frac{\partial LS_{it}}{\partial \mu_{it}} > 0 \; if \, \frac{\phi_{it}}{(1 - \phi_{it})} > \frac{\theta_{it}^{L}}{\theta_{it}^{K} + \theta_{it}^{M}}.$$

Hence, if the relative bargaining power of workers, $\frac{\phi_{it}}{(1-\phi_{it})}$, is sufficiently strong, firm-level labor shares grow in response to increases in markups. Note that the denominator of the right-hand side depends on the specifications of profits in the bargaining. If bargaining is modelled in terms of short-run profits (that exclude capital), equation (B.14) will be expressed in terms of the labor and intermediate input output supply elasticities: $\frac{\partial LS_{it}}{\partial \mu_{it}} > 0 \; if \; \frac{\phi_{it}}{(1-\phi_{it})} > \frac{\theta_{it}^{L}}{\theta_{it}^{M}}$.

Appendix B.2.4: Size-dependent bargaining power

Here, we extend the model from Appendix B.2.2 such that workers' bargaining power declines with firms' size. This assumption is supported by empirical evidence. Mertens et al. (2022) use the same German manufacturing data that we use and show that larger firms do indeed have lower rent-sharing elasticities. This section shall illustrate how interactions between labor and product market power (i.e., rent-sharing) can offer an explanation for why markups can fall with firm size (without violating Marshall's second law of demand). Importantly, we do not intend to write up a full model here as this goes beyond the scope of our study. We rather illustrate basic concepts and isolate key mechanisms. Formally, we write the bargaining model as:

(B.15) $$\underset{Q_{it}}{Max}\ \phi_{it}(Q_{it})log(w_{it}L_{it}) + [1-\phi_{it}(Q_{it})]\log(P_{it}Q_{it} - C_{it}),$$

where C_{it} denotes the cost function.[32] Taking the first order condition with respect to quantity and rearranging yields:

(B.16) $$\frac{\delta P_{it}}{\delta Q_{it}}Q_{it} + P_{it} - \frac{\delta C_{it}}{\delta Q_{it}} = \frac{\phi'(Q_{it})}{1-\phi(Q_{it})}log\left(\frac{\Pi_{it}}{w_{it}L_{it}}\right)\Pi_{it}.$$

Define $\tilde{\mu}_{it} \equiv \frac{1}{1+\frac{\delta P_{it}Q_{it}}{\delta Q_{it}P_{it}}}$ as the markup consistent with the markup rule, which does not hold in this model. Importantly, combining the markup rule with the optimal condition for intermediate inputs, one can show that the usual markup estimator is

[32] Workers are assumed to have no outside option to simplify the algebra.

robust to this specification. Thus, we can use this model to interpret our results without contradiction. Combining (B.16) with the markup rule yields:

$$\frac{1}{\tilde{\mu}_{it}} - \frac{1}{\mu_{it}} = \frac{\phi'(Q_{it})}{1-\phi(Q_{it})} log\left(\frac{\Pi_{it}}{w_{it}L_{it}}\right)\frac{\Pi_{it}}{P_{it}} \quad \text{(B.17)}$$

If worker power falls in firm size, i.e. $\phi'(Q_{it}) < 0$, optimal markups are smaller than markups implied by the slope of the product demand. Moreover, this distance grows in firm size and profitability. Intuitively, firms have an incentive to keep markups low and to expand in terms of market shares, such that they gain a more dominant labor market position and can reduce rent-sharing. This illustrates how interactions between firms' product and labor market power can help to explain our highly robust finding of a negative cross-sectional correlation between markups and firm size.

Appendix C: Estimating Output Elasticities in the German firm data

The following approach is closely in line with Mertens (2020, 2022a) and follows Olley & Pakes (1996), Wooldridge (2009), and De Loecker et al. (2016). Online Appendix A.1 defines all variables used in this sections.

Production model

The translog production model we apply writes:

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

Lower case letters denote logs. $\boldsymbol{\phi}'_{it}$ captures the production inputs, K_{it}, L_{it}, and M_{it}, and its interactions.[33] ε_{it} is an i.i.d. error term. 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. We allow that firms' input decisions for intermediates depends on productivity shocks. Labor and capital do not respond to contemporary productivity shocks and are thus quasi-fixed inputs. The timing assumption on labor addresses that our employment variable refers to employment at the end of September, whereas all other variables pertain to the full calendar year. Moreover, it is consistent with Germany's inflexible labor market setting and the presence of worker-side labor market power (see Appendix

[33] The production function is: $q_{it} = \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} + \beta_{ll} l_{it}^2 + \beta_{mm} m_{it}^2 + \beta_{kk} k_{it}^2 + \beta_{lk} l_{it} k_{it} + \beta_{lm} l_{it} m_{it} + \beta_{km} k_{it} m_{it} + \beta_{lkm} l_{it} k_{it} m_{it} + \omega_{it} + \varepsilon_{it}$, 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.

B.2.2).[34] However, all our results hold when allowing for flexible labor. This is not surprising because it is well-documented that variation in markups and markdowns is mostly driven by input expenditure shares (De Loecker 2021).[35]

There are three issues preventing us from directly estimating the production function (C.1) with OLS:

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

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

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

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, we construct a firm-specific price index from observed output price information following Eslava et al. (2004). We use this price index to purged observed

[34] Also other studies rely on quasi-fixed labor (e.g., De Loecker et al. (2016)). The appropriate timing assumptions on inputs always depend on the underlying setting and institutions.
[35] See also Appendix D.2.6 for how input shares relate to firm size.

firm revenue (for single- and multi-product firms) from price variation by deflating firm revenues with this price index.[36] Specifically, we construct firm-specific Törnqvist price indices for each firm's composite revenue from its various products:

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

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 last year. We define the first year in the data as the base year, i.e. $\pi_{t=1995} = 100$. For firms entering after 1995, we follow Eslava et al. (2004) in using an industry average of our firm price indices as a starting value. Similarly, we 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, we end up with a quasi-quantity measure of output, for which, with slightly abusing notation, we keep using q_{it}.

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

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

Solving issue 2: Controlling for unobserved input price variation

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

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

Comments on the notation are in order. $B_{it}(.) = B_{it}\big((\pi_{it}, ms_{it}, G_{it}, D_{it}) \times \boldsymbol{\phi}^{c}_{it}\big)$ 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}). $\boldsymbol{\phi}^{c}_{it} = \{1; \widetilde{\boldsymbol{\phi}}_{it}\}$, 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 $\boldsymbol{\phi}^{c}_{it}$ 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, we assume that product prices and market shares contain information about product quality and that producing high-quality products requires expensive high-quality inputs. As 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, we 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 $B(.)$, we 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 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 we apply is that De Loecker et al. (2016) estimate product-level production functions, whereas we transfer their framework to the firm-level. To do so, we 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, we 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.

[38] We 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.

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 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, we employ a control function approach in the spirit of Olley & Pakes (1996) and Levinsohn & Petrin (2003). We base our control function on firms' consumption of raw materials, which we denote both with e_{it} and which are components of total intermediate inputs. Inverting the demand function for e_{it} yields an expression for productivity:

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

$\mathbf{\Gamma}_{it}$ 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}. We include dummy variables for export activities (EX_{it}), 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} (assuming that input prices are correlated with each other).

Recap that productivity follows a first order Markov process. We 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 we 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) yields:

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

which constitutes the basis of our estimation.

Identifying moments

We estimate equation (C.5) 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}.

[39] $\boldsymbol{T}_{it}$ and $\mathbf{\Gamma}_{it}$ both include the export dummy and the number of products a firm produces. This constitutes no problem for our estimation, as we are not interested in identifying the coefficients from the control functions.

[40] We approximate $h_{it}(.)$ by a third order polynomial in all of its elements, except for the variables in $\mathbf{\Gamma}_{it}$. Those we add linearly. $B_{it}(.)$ is approximated by a flexible polynomial where we interact the output price index with elements in $\widetilde{\boldsymbol{\phi}}_{it}$ 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 $\widetilde{\boldsymbol{\phi}}_{it}$ would create too many parameters to be estimated. This implementation is similar to De Loecker et al. (2016).

Similarly, we use lagged values of terms including firms' market share and output price index as instruments for their contemporary values as we consider these to be flexible variables.[41] We define identifying moments jointly for 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 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:

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

where for convenience we defined:

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

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

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

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

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

---

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

w_{it} denotes the average wage a firm pays.[42] We derive output elasticities from the production function as $\frac{\partial q_{it}}{\partial x_{it}} = \theta_{it}^{X}$ for $x = \{l, k, m\}$ and $X = \{L, K, M\}$. Median (mean) output elasticities for labor, capital, and intermediates across all industries equal 0.30 (0.29), 0.11 (0.11), 0.64 (0.64), respectively.[43] We then use equations (1) and (2) from the main text to estimate markups and markdowns. Finally, we tested various other estimation approaches, allowing for different timing assumptions (e.g., flexible labor) and using different estimation routines (cost-shares, OLS), all yielding qualitatively similar results. See also online Appendix D.2.3 for a time-varying translog production model.[44]

[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] We drop observations with negative output elasticities as they are inconsistent with the production model we assume. This amounts to 5,797 (2.34%) of observations.

[44] We also do not purge measurement error and unanticipated shocks from output when estimating markups as this did not changes our results (results with the error correction are available on request).

Appendix D: Additional results

Appendix D.1: Summary statistics (German data)

TABLE D.1

SUMMARY STATISTICS FOR SAMPLE FIRMS, GERMAN MANUFACTURING SECTOR DATA						
	Mean	Sd	P25	Median	P75	Observations
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Markups	1.10	0.04	0.98	1.07	1.19	242,303
Labor markdowns	1.00	0.26	0.66	0.90	1.22	242,303
Number of employees	304.28	2,223.95	47	94	224	242,303
Number of products	3.60	6.73	1	2	4	242,303
Log labor productivity	10.55	0.77	10.12	10.61	11.06	221,816
Labor share (value-added over wages)	0.78	0.07	0.63	0.76	0.88	242,303
Deflated intermediate input expenditures per employee in thousands	96.96	654,000	44.10	73.05	122.07	242,303
Deflated capital per employee in thousands	95.97	923,000	38.01	68.54	119.88	242,303

Notes: Table D.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. German manufacturing sector micro data. 1995-2016.

Appendix D.2: Additional results

Appendix D.2.1: Using sales market shares as size measure (German data)

MARKUPS AND FIRMS' MARKET SHARES, GERMAN MANUFACTURING SECTOR

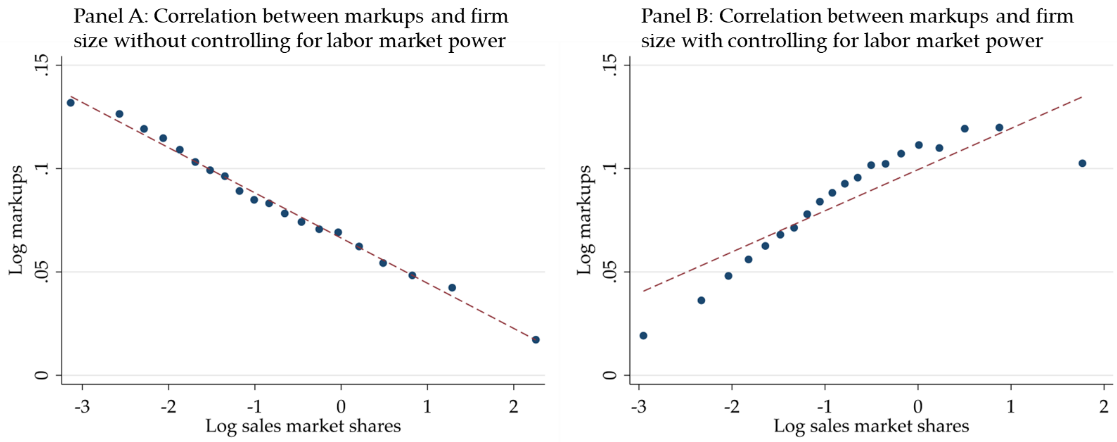

FIGURE D.1 – Binned scatter plots from firm-level regressions of log markups on log firm industry sales shares and log markdowns while controlling for year and four-digit industry fixed effects. Panel A (B) shows results from projecting markups on firm market shares without (with) controlling for firms' markdowns. German manufacturing sector data. 1995-2016. 242,303 firm-year observations.

TABLE D.2

MARKUPS AND MARKET SHARES

	Log Markups			
	(1)	(2)	(5)	(6)
Log sales market share	-0.022***	0.020***	-0.014***	0.024***
	(0.001)	(0.001)	(0.001)	(0.001)
Log markdowns		-0.247***		-0.246***
		(0.003)		(0.004)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Product FE	No	No	Yes	Yes
Single product firms	No	No	Yes	Yes
Observations	242,303	242,303	82,942	82,942
R-squared	0.147	0.447	0.334	0.559
Num. firms	44,600	44,600	17,855	17,855

Notes: Table D.2 reports results from projecting firm markups on firms' industry sales shares. Columns 1-2 show results for the full sample. Columns 3-4 show results for the single product firm sample. German manufacturing sector data. 1995-2016. Standard errors are reported in parentheses and clustered at the firm level. Significance: *10 percent, **5 percent, ***1 percent.

Appendix D.2.2: Markup-size correlations for subgroups (German data)

Table D.3 reports the coefficients on firm size from the baseline regressions from Table 2, columns 1 and 2 for various firm groups. We always control for industry and year fixed effects.

TABLE D.3

MARKUPS AND FIRM SIZE FOR VARIOUS SUBGROUPS

Subgroup of firms	Coefficient on firm size without controlling for markdowns (1)	Coefficient on firm size with controlling for markdowns (2)	Number of observations (3)
Consumer good producers	-0.014*** (0.001)	0.015*** (0.001)	64,998
Intermediate good producers	-0.025*** (0.001)	0.017*** (0.01)	102,324
Investment good producers	-0.026*** (0.001)	0.037*** (0.01)	73,752
Exporter	-0.020*** (0.001)	0.023*** (0.001)	188,285
Non-Exporter	-0.027*** (0.001)	0.021*** (0.001)	54,014

Notes: Table D.3 reports regression coefficients on firm size from projecting firm markups on firms' size (sales) while controlling for year and industry fixed effects. Columns 1 and 2 report results without and with controlling for labor markdowns, respectively. Column 3 reports the number of observations entering the regressions. German manufacturing sector data. 1995-2016. Standard errors are reported in parentheses and clustered at the firm level. Significance: *10 percent, **5 percent, ***1 percent.

Appendix D.2.3: Time-varying production function (German data)

One restriction of the production model that we use for the German micro data is that it assumes time-constant production function parameters (it still allows for time-varying output elasticities). As a result, we abstract from biased technological change. De Loecker et al. (2020) suggest a simple way to allow for time-varying production function coefficients by estimating the production function by separate year windows. As they argue, this allows for a restricted form of biased technological change at the industry-level (De Loecker et al. (2020, p.628)). We follow their approach and estimate the translog production model explained in online Appendix C by five-year rolling time windows (we exclude the first and last two years). Figure D.2 and Table D.3 show the associated results from this specification. As can be seen, the results look extremely similar to our baseline results. Hence, allowing for industry-specific biased technological change does not affect our conclusions.

MARKUPS AND FIRM SIZE, ALLOWING FOR TIME-VARYING PRODUCTION FUNCTION COEFFICIENTS, GERMAN MANUFACTURING SECTOR

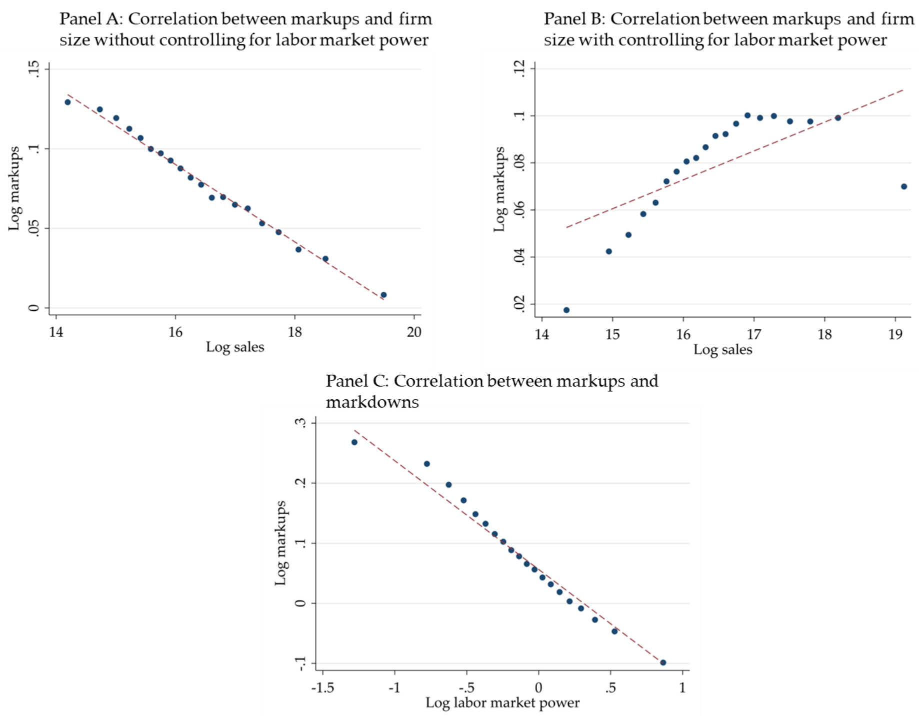

FIGURE D.2 – Binned scatter plots from firm-level regressions of log markups on log firm size and log markdowns while controlling for year and four-digit industry fixed effects. Panel A (B) shows results from projecting markups on firm size without (with) controlling for firms' markdowns. Panel C shows results from regressing markups on markdowns. Markups and markdowns are derived from a translog production function that allows for time-varying coefficients. German manufacturing sector data. 1997-2014. 190,295 firm-year observations.

TABLE D.4

MARKUPS AND FIRM SIZE, USING A TIME-VARYING PRODUCTION MODEL								
	Log Markups							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log sales	-0.024***	0.012***			-0.023***	0.019***		
	(0.001)	(0.001)			(0.001)	(0.002)		
Log employment			-0.027***	0.014***			-0.025***	0.022***
			(0.001)	(0.001)			(0.002)	(0.002)
Log markdowns		-0.197***		-0.194***		-0.195***		-0.192***
		(0.002)		(0.002)		(0.005)		(0.004)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Product FE	No	No	No	No	Yes	Yes	Yes	Yes
Single product firms	No	No	No	No	Yes	Yes	Yes	Yes
Observations	190,295	190,295	190,295	190,295	64,588	64,588	64,588	64,588
R-squared	0.140	0.389	0.132	0.389	0.315	0.502	0.311	0.501
Num. firms	37,695	37,695	37,695	37,695	14,789	14,789	14,789	14,789

Notes: Table D.4 reports results from projecting firm markups on firm size when using a time-varying production model to estimate markups. Columns 1-4 show results for the full sample. Columns 5-8 show results for the single product firm sample. German manufacturing sector data. 1997-2014. Standard errors are reported in parentheses and clustered at the firm level. Significance: *10 percent, **5 percent, ***1 percent.

Appendix D.2.4: Wage markdowns and firm size (German and CompNet data)

Figure D.3 shows the correlation between wage markdowns and firm size in the German data. Figure D.4 reproduces this correlation for our European CompNet data.[45]

[45] Mertens (2022b) provides further discussion on the relation of labor market power with average firm wages in Europe.

WAGE MARKDOWNS AND FIRM SIZE, GERMAN MANUFACTURING SECTOR

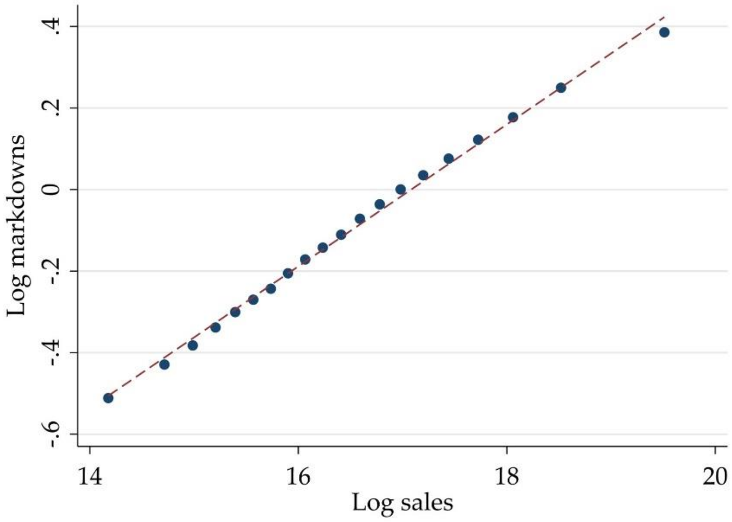

FIGURE D.3 – Binned scatter plots from firm-level regressions of log wage markdowns on log firm size (sales) while controlling for year and four-digit industry fixed effects. German manufacturing sector. 1995-2016. 242,303 firm-year observations.

WAGE MARKDOWNS AND FIRM SIZE, EUROPEAN COUNTRIES

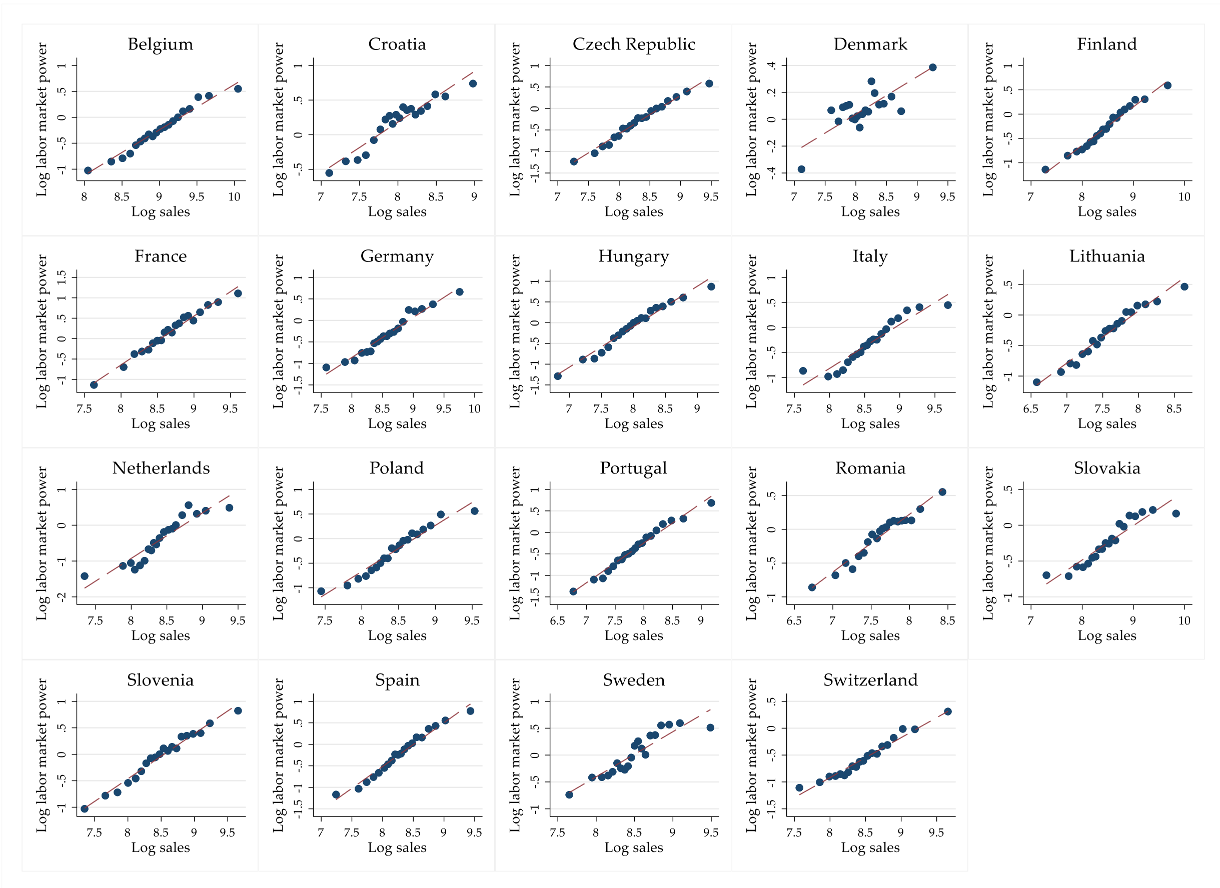

FIGURE D.4 – Binned scatter plots from quintile-level regressions of median wage markdowns on median firm size along quintiles of the sales distributions within two-digit industries (all in logs). All regressions control for year and industry fixed effects. CompNet data 1999-2018. Yearly and sectoral coverage varies by country as described in Table 2 of the main text.

Appendix D.2.5: Other markup estimators used in the literature (German data)

In the main text, we discuss that several studies rely on biased estimates of markups if labor markets are imperfect. Here, we show that we can reproduce the positive correlation between firm size and these biased markup measures that has been documented in the literature. Figure D.5 relies on the markup equation (4) of the main text: $\mu_{it}^{L} = \mu_{it}\gamma_{it} = \theta_{it}^{L}\frac{P_{it}Q_{it}}{w_{it}L_{it}}$, which, among others, is used in Autor et al. (2020), whereas Figure D.6 relies on the markup expression $\mu_{it}^{DLEU} = ((\theta_{it}^{M} + \theta_{it}^{L})/(\theta_{it}^{M}\gamma_{it} + \theta_{it}^{L}))\mu_{it}\gamma_{it}$, which conceptionally replicates the markup expression in De Loecker et al. (2020).[46] Note that both markup expression (or input wedges) combine markups and labor market power into one expression. Together with our previous results (main text and Appendix D.2.4), we can conclude that the positive correlation in Figures D.5 and D.6 is driven by a positive correlation between wage markdowns and firm size and does not reflect a positive correlation between markups and firm size.

[46] We derive μ_{it}^{DLEU} from our production function estimates. De Loecker et al. (2020), instead estimate a production function combining labor and intermediates into one "variable" production factor. If this variable production factor contains only labor and intermediate inputs (or the respective input expenditures), if intermediates input prices are exogenous to firms, and if the underlying assumptions of combining labor and intermediates into one joint production factor (e.g., perfect substitutability between both inputs) are true, both approaches will yield the same result.

FIRM SIZE AND MARKUPS BASED ON THE FOC OF LABOR, GERMAN MANUFACTURING SECTOR

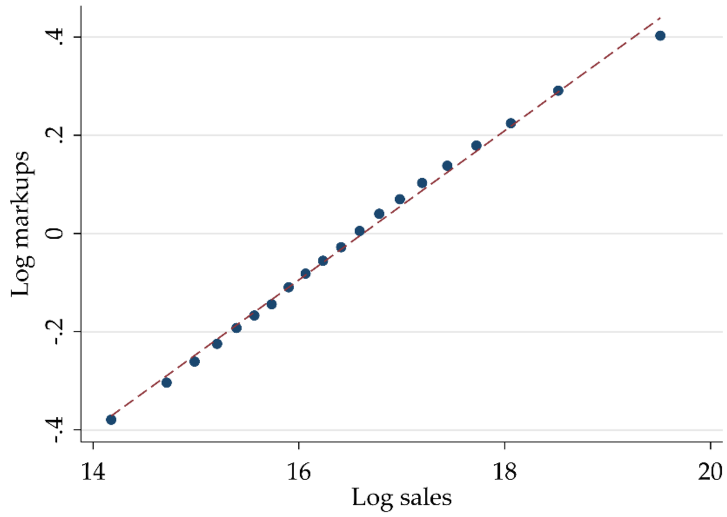

FIGURE D.5 – Binned scatter plots from firm-level regressions of logged labor input wedges (μ_{it}^{L}) on log firm size (sales) while controlling for year and four-digit industry fixed effects. Labor input wedges jointly reflect markups and wage markdowns ($\mu_{it}^{L} = \mu_{it}\gamma_{it} = \theta_{it}^{L}\frac{P_{it}Q_{it}}{w_{it}L_{it}}$). German manufacturing sector. 1995-2016. 242,303 firm-year observations.

FIRM SIZE AND MARKUPS BASED ON FIRMS' JOINT INPUT DECISION FOR INTERMEDIATES AND LABOR, GERMAN MANUFACTURING SECTOR

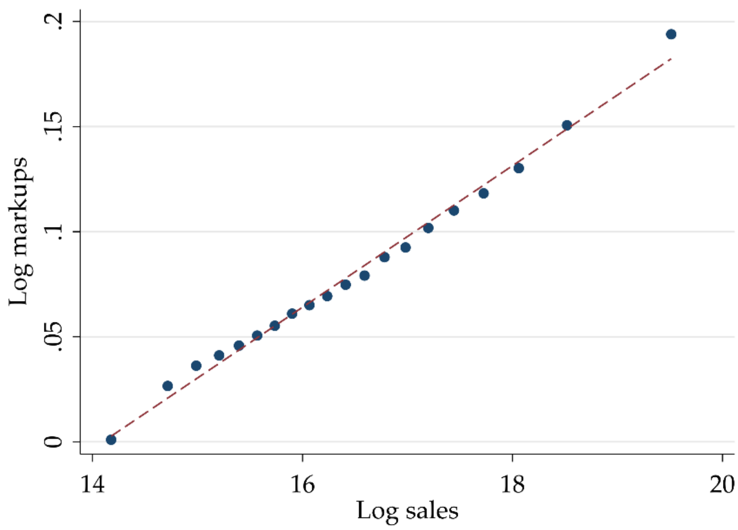

FIGURE D.6 – Binned scatter plots from firm-level regressions of the log of combined labor and intermediate input wedges (μ_{it}^{DLEU}) on log size (sales) while controlling for year and four-digit industry fixed effects. These input wedges jointly reflect markups and wage markdowns and are derived using the formula $\mu_{it}^{DLEU} = ((\theta_{it}^{M} + \theta_{it}^{L})/(\theta_{it}^{M}\gamma_{it} + \theta_{it}^{L}))\mu_{it}\gamma_{it}$. German manufacturing sector. 1995-2016. 242,303 firm-year observations.

Appendix D.2.6: Input shares and firm size (German data)

Figure D.7 projects the ratio of sales over intermediates and sales over labor costs on firm size. The former ratio captures a simple measure of markup-variation when output elasticities are constant across firms (see equation (1) of the main text). The second ratio reflects a simple measure of combined markup and wage markdown variation (see equation (4) of the main text). As expected, we find a negative correlation between firm size and sales over intermediates and a positive correlation between firm size and sales over labor costs (which is driven by a positive correlation between wage markdowns and firm size).

INPUT SHARES AND FIRM SIZE, GERMAN MANUFACTURING SECTOR

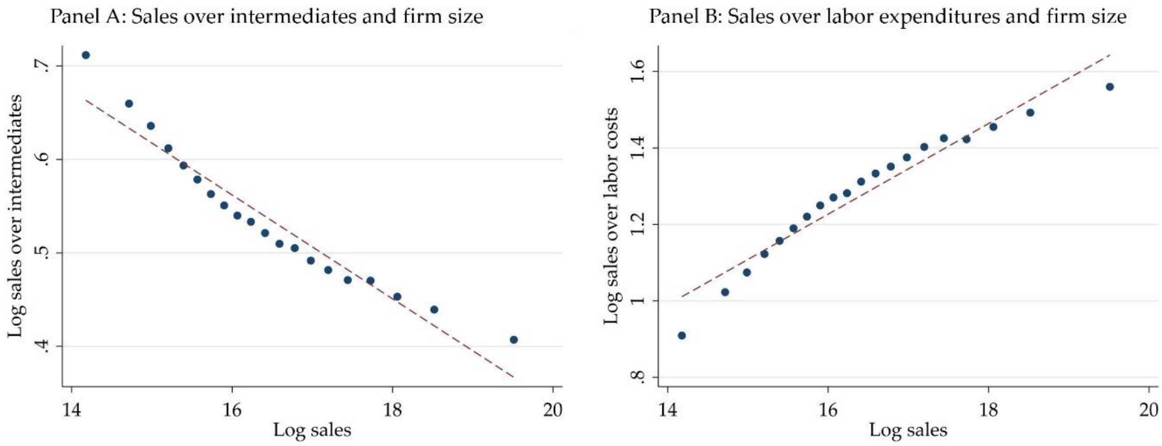

FIGURE D.7 – Binned scatter plots from firm-level regressions of log input shares on log firm size (sales) while controlling for year and four-digit industry fixed effects. Panel A (B) shows results from projecting sales over intermediate (labor) input expenditures on firm size. German manufacturing sector data. 1995-2016. 242,303 firm-year observations.

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