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Micro-mechanisms behind declining labor shares: Rising market power and changing modes of production ☆

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ABSTRACT

I derive a micro-founded framework showing how rising firm market power on product and labor markets and falling aggregate labor output elasticities provide three competing explanations for falling labor shares. I apply my framework to 20 years of German manufacturing sector micro data containing firm-specific price information to study these three distinct drivers of declining labor shares. I document a severe increase in firms' labor market power, whereas firms' product market power stayed comparably low. Changes in firm market power and a falling aggregate labor output elasticity each account for one half of the decline in labor's share.

1. Introduction

Research has documented a worldwide decline in labor's share in economic output (Karabarbounis and Neiman, 2013; Dao et al., 2017). This not only has severe distributional consequences, but also raises doubts on widely applied Cobb-Douglas production models relying on constant output elasticities of input factors. Not least, the decline in labor shares poses questions about the meaning of work and the future role of people in the economic activities of our society. Therefore, it is unsurprising that a substantial body of literature debates the causes behind the global decline of wage shares.

Traditionally, research explains falling labor shares through changes in firms' mode of production that reduce the importance of labor to firms. These changes are often seen as a result of biased technological change (Acemoglu, 2003; Oberfield and Raval, 2021), declining relative capital prices (Karabarbounis and Neiman, 2013), or globalization, which facilitates the offshoring of domestic production activities (Harrison, 2005; Elsby et al., 2013). Other work highlights the erosion

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of labor market institutions (Blanchard and Giavazzi, 2003) and discusses the role of measurement error in explaining declining labor shares (Koh et al., 2020). Most recently, the literature discusses whether rising product markups and firm concentration contributed to falling labor shares (De Loecker and Eeckhout, 2020; De Loecker et al., 2020, henceforth DLEU, Autor et al., 2020).

Yet, despite substantial work, the quantitative importance of the individual channels causing falling labor shares remains not well understood. This study provides such a quantification using a micro-econometric production side framework nesting most of the currently debated mechanisms behind declining labor shares into a parsimonious framework. My framework offers three competing explanations for a fall of labor's share: i) a fall in firms' labor output elasticities, capturing changes in firms' mode of production associated with a decreasing importance of labor to firms, ii) an increase in firms' product market power, or iii) an increase in firms' labor market power. The latter two explanations refer to an increase in market distortions and reflect inefficient scenarios.[1] In contrast, a decrease in labor's output elasticity causes a fall in the wage share even within a competitive environment. In this case, a fall in labor's share results from an aggregate output maximizing reallocation of factor shares.

To study these three distinct drivers of changes in labor's share, I use 20 years of micro-data on German manufacturing sectors firms starting in 1995. This dataset contains information on firms' product quantities and prices, making the data perfectly suited for my study as it allows me to measure *firm-specific* price variation, which is crucial for calculating unbiased measures of market power parameters and output elasticities (De Loecker et al., 2016, henceforth DLGKP)). In most studies, such information is not accessible.[2]

From applying my framework, I provide two novel insights. First, by decomposing firm market power into product and labor market power, I show that, coinciding with the fall of labor's share, there is a high and rising degree of aggregate firm *labor* market power, whereas aggregate *product* market power, although moderately increasing, stays low. This constitutes important evidence for the debate on rising firm market power and its role for falling labor shares put forward by De Loecker and Eeckhout (2020) and DLEU, who document a severe increase in firm market power throughout the world (particularly in the US) that coincides with the fall of labor shares.[3] Most of this debate abstracts from labor market imperfections.[4] As consequence, variation in labor's share that does not result from a changing technological importance of labor is by design attributed to *product* market power. My findings of slightly increasing product market power and strongly rising labor market power challenge this conclusion and point to a key role for labor market power in explaining the documented fall of labor's share.

Furthermore, by assuming competitive labor markets, the existing literature cannot determine whether rising firm market power results from product or labor markets. Clarifying this, as I do, is important because policies targeting output market power differ from policies targeting labor market power. And indeed, my estimates show that labor market power is the more important source of (growing) firm market power in the German manufacturing sector. Whereas I cannot infer on the much-discussed rise of market power in the US, my findings demonstrate that incorporating labor market power into the analysis is crucial for understanding rising firm market power and its macroeconomic implications.

Second, I use my framework to quantify the contribution of market power and changing production processes to the declining wage share. This assessment is informative on the quantitative importance of market power and changing modes of production in explaining a fall of labor's share.[5] I answer this question using a simple thought experiment: If a declining labor share results from efficient changes in firms' production processes, the aggregate labor output elasticity decreases in concordance with labor's share. If the labor share, however, falls due to an increase in firms' product or labor market power, one observes a wedge between the wage share and the aggregate labor output elasticity. Applying this idea, I find that half of the decline in Germany's manufacturing sector labor share between 1995 and 2014 is explained by a decrease in the output elasticity of labor. The other half is accounted for by increasing firm market power. Given my estimates of product and labor market power, I infer that most of the contribution of market power results from growing labor market power. Notably, the falling aggregate labor output elasticity results from declining labor output elasticities within most industries and not from reallocation processes between industries. This supports studies causing doubts on production models featuring time-constant output elasticities of production factors, as most applied Cobb-Douglas specifications (Chirinko et al., 2011; Raval, 2019).

In addition to the mentioned literature, my study relates to a substantial body of work on changes in labor's share dating back at least to Kaldor (1955–56, 1957), who established the stability of the labor share as one of his famous stylized facts for economic growth. Already in 1958 (Solow, 1958), published a "skeptical note" on the presumed constancy of factor

[1] Whereas rising firm product market power indirectly affects labor shares through a reduction in firms' labor demand resulting from a reduction in firms' output, an increase in firms' labor market power directly reduces labor shares because firms with labor market power reduce their labor demand to drive wages below competitive levels.

[2] Despite I focus on manufacturing to utilize this rich data, my results are informative on the general debate on falling labor shares. In most countries, declining manufacturing sector labor shares explain large parts of declining aggregate labor shares (Dao et al. (2017)). Hence, understanding manufacturing sector labor shares is key for understanding aggregate labor shares.

[3] Karabarbounis and Neiman (2013) and Barkai (2020) have also mentioned rising markups as a potential cause for falling labor shares.

[4] Recent exceptions are Gouin-Bonenfant (2020) and Brooks et al. (2021).

[5] This complements Karabarbounis and Neiman (2013) and Dixon and Lim (2020), who, without having direct measures of firm-level markups provide a similar assessment using a macroeconomic framework.

shares. In earlier work, Keynes (1939) called the factor share stability "a bit of a miracle".[6] Whereas much of the work in this field focuses on macroeconomic frameworks, my article belongs to a young literature using micro-data to analyze movements of labor's share (e.g. DLEU; Autor et al., 2020; Kehrig and Vincent, 2021; Oberfield and Raval, 2021). The main advantage of using micro-data is that it allows to study the distribution of variables across firms. This is important for understanding the causes of changes in labor's share, labor's output elasticity, and aggregate product and labor market power, which, as I highlight, is central for deriving policy implications.

Finally, my work relates to a fast-growing literature emphasizing labor market power as an alternative source of firm market power and which recently raised concerns that labor market power creates substantial welfare losses that are comparable to those from product market power (e.g. Naidu et al., 2018; Berger et al., 2019; Azar et al., 2020).[7] My article contributes to this research strand by providing insights on how reallocation processes between firms contributed to a severe increase in aggregate labor market power over the past decades in Germany. Furthermore, by linking a direct and firm-specific measure of labor market power to movements of labor's share, my study offers novel insights on the macroeconomic relevance of (growing) firm labor market power.[8]

The remainder proceeds as follows: Section 2 describes the data. Section 3 derives my framework from which I infer on the mechanisms behind declining labor shares. Section 4 presents descriptive evidence, conducts decomposition exercises, and calculates the contribution of rising market power and changing modes of production to the fall of the labor share. Section 5 provides additional discussion and robustness tests. Section 6 concludes.

2. Data

I use an administrative yearly panel dataset on German manufacturing sector firms with more than 20 employees from 1995 to 2014. The data are supplied by the statistical offices of Germany. As firms are obliged to report by law, the data are of comparably high quality and contain only a negligible amount of missing values. Among others, the data contain information on firm-level costs, investment, revenues, employment, and product prices and quantities. To limit administrative burden, some variables are only collected for a representative and periodically rotating subsample covering 40% of all manufacturing firms with more than 20 employees. This includes information on intermediate input expenditures or labor costs by various categories.[9] The online Appendix C.1 details the definitions of all variables used during my analysis and provides information on data access.

By using such a long time span of firm-level data, I face a problem with respect to the time-consistent classification of firms into industry sectors. This is because the NACE sector classification changed in 2002 and 2008. As I am interested in explaining wage shares with firm-level data over time, and as the procedure to recover output elasticities and market power parameters relies on time-consistent industry codes, having a time-consistent industry classification is vital to my study. Recovering such an industry classification from official concordance tables is, however, problematic as they contain many ambiguous sector reclassifications.

To solve this problem, I use information on firms' product mix to classify all firms into NACE rev 1.1 sectors based on their main production activities.[10] This procedure works because the first four digits of the nine-digit GP product classification reported in AFiD are identical to the NACE sector classification. Applying this method still demands a consistent reclassification of all products into the GP2002 scheme. Reclassifying products is, however, less ambiguous than reclassifying industries. Moreover, in ambiguous cases, I can follow the firm-specific product mix over the reclassification periods to unambiguously reclassify most products (I observe what firms produce before and after reclassifications). Having constructed the product-industry classification, I attribute every firm to the industry in which it generates most of its revenue. The statistical offices of Germany use a similar approach to classify firms into industries. When comparing my and the statistical offices' classification 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 respectively matches the statistical offices' classification in 95% and 86% of all cases.

Using my data, Fig. 1 shows how value-added and revenue wage shares evolved in Germany's manufacturing sector. Between 1995 and 2014, revenue (value-added) wage shares declined by 18 (9) percent, corresponding to an absolute decline of the revenue (value-added) labor share from 0.270 (0.762) to 0.222 (0.692).[11]

Note the spike during the crisis in 2009. Intuitively, this phenomenon reflects sticky wage and labor quantity adjustments (i.e. labor hoarding) in response to negative output shocks. The percentagewise stronger decline in the revenue wage

[6] See Giovannoni (2014a, 2014b) for a comprehensive review beyond the mentioned studies.

[7] Recently, there has been renewed interest in studying labor market power. The discussion on it as an alternative form of firm market power dates back to Robinson (1933). Ashenfelter et al., 2010 provide a review.

[8] Research often maps measurable market concentration to labor market power (e.g. Berger et al. (2019); Azar et al. (2020)). I directly calculate firms' labor market power from wedges between wages and marginal revenue products of labor without invoking such implicit links.

[9] I clean the firm data from outliers in value-added over revenue and deflated sales over production inputs and from observations with negative value-added. I purge the product data (separately given) from outliers in terms of price growth and price deviation from the average product price.

[10] I thank Richard Bräuer with whom I developed this classification crosswalk.

[11] Manufacturing accounts for stable 22% of Germany's GDP. The economy-wide revenue (value-added) labor share fell from 0.24 to 0.20 (0.59 to 0.57), which is largely caused by the manufacturing sector. Reallocation patterns between one-digit sectors have only a small effect on the aggregate labor share (see online Appendix I).

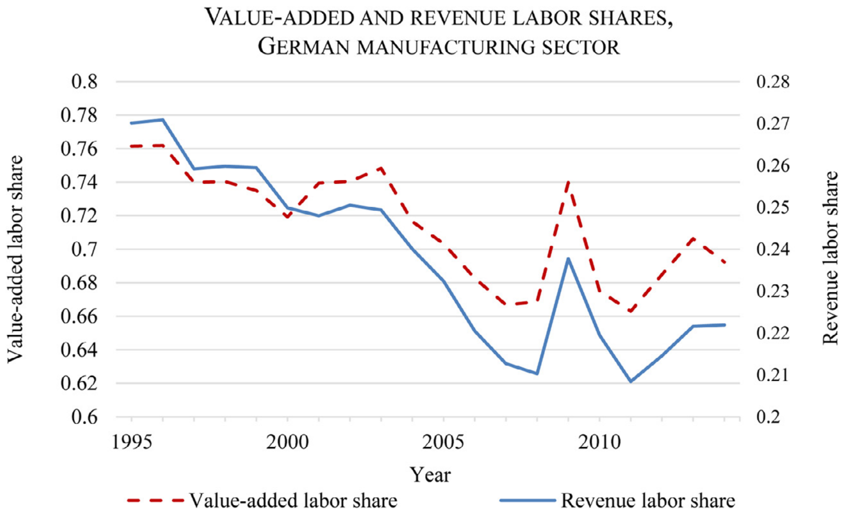

Fig. 1. Value-added and revenue labor shares in the German manufacturing sector. Sample firms.

share indicates a decrease of firms' value-added depth (the revenue over value-added ratio). However, I focus on potential mechanisms behind changes in labor's share at a later point. Beforehand, the next section shows how labor shares relate to market power and the importance of labor in firms' production processes.

3. A production-side framework for the labor share

This section derives my micro-econometric framework connecting labor shares to labor output elasticities and firms' product and labor market power. Section 3.1 derives key equations for this framework and discusses its assumptions. My approach builds upon Dobbelaere and Mairesse (2013) and DLEU. Section 3.2 links my framework to existing work on rising market power. Section 3.3 explains how I separate the contribution of rising market power and a falling technological importance of labor to a decline in labor's share. Section 3.4 recovers necessary parameters from the data.

3.1. Theoretical framework

A firm i produces physical output in period t using the production function:

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

Q_{it} represents total physical output and L_{it}, K_{it}, and M_{it} denote labor, capital, and intermediate inputs used in the production of Q_{it}. Firm-specific total factor productivity is denoted by ω_{it}. The only restriction on the functional form of (1) is that it is twice differentiable.

Eq. (1) describes a physical production process. A production model transforming physical inputs into physical outputs approximates firms' production technology more closely than a value-added specification, simply because there is no market for value-added.[12]

Firms demand labor on imperfectly competitive labor markets. Following most of the literature, I assume that intermediate input markets are flexible and that intermediate input prices are exogenous to firms.[13] For the remainder, I abstract from capital market imperfections and focus on labor markets imperfections because labor market power will be of key interest when discussing declining labor shares.

As shown by a large labor market literature, labor market power (γ_{it}) translates into wedges between marginal revenue products of labor and wages:

$$\gamma_{it} = \frac{MRPL_{it}}{w_{it}}. \tag{2}$$

w_{it} and $MRPL_{it}$ denote the wage and the marginal revenue product of labor. The existence of such a wedge signals labor market power as it reflects an inefficient distortion of rents towards the firm ($\gamma_{it} > 1$) or its employees ($\gamma_{it} < 1$). To provide

[12] Bruno (1978) showed that it demands restrictive assumptions for the existence of a value-added production function. For a discussion on different production concepts, see Bruno (1978) and Diewert (1978).

[13] Conditional on these two assumptions, this allows for suppliers of intermediate inputs charging a markup over marginal costs, leading to double marginalization (DLEU). When aggregating, I use sales and cost weights for aggregating market power parameters. As opposed to value-added weights, this accounts for intermediate input suppliers' markups when aggregating firm-level markups.

more intuition, I present two models on how labor market imperfections translate into labor market power as defined in Eq. (2) in the online Appendix A.

With respect to the factors driving labor market power, I stay agnostic. I am interested in the extent of labor market power, its evolution, and distribution across firms, instead of the factors causing it. Yet, I study potential factors creating labor market power in online Appendix H and show that market concentration, firm size, and firms' capital intensity are positively correlated with firm labor market power. Moreover, firms located in regions characterized by a lower union density and a lower rate of collective wage agreements (East Germany) possess higher labor market power conditional on several controls.

Despite this is consistent with defining γ_{it} as labor market power, γ_{it} also captures firms' adjustment costs. Firm-side adjustment costs can either be *related or unrelated* to labor market power. Adjustment costs related to labor market power are the main source of worker-side labor market power because without firms facing hiring/firing frictions, workers cannot bargain for wages above the MRPL (as workers could then be easily replace when starting to bargain). This key concept underlies all models featuring worker-side labor market power and is often modelled as workers coordinating their labor supply, e.g. through unions as in Mcdonald and Solow (1981), or as workers having firm-specific human capital that is costly to build (e.g. Kline et al., 2019). Lately, Garin and Silvério (2019) provided a general theoretical framework illustrating this fact. In my framework that allows for worker- and firm-side labor market power, I want to capture these adjustment costs related to labor market power in γ_{it}.

Consequently, one could view Eq. (2) not just as an outcome of a static optimization problem, but rather as a first order condition of a (potentially) dynamic problem, where γ_{it} is a function of all factors creating firm- and worker-side labor market power, including adjustment frictions related to labor market power as well as factors causing firm monopsony power (e.g. concentration, job preferences).[14] Nevertheless, a potential concern for my analysis are adjustment frictions *unrelated* to labor market power. I discuss this further in Section 5 and conclude that it is unlikely that such adjustment costs can explain my findings as I focus on *changes over time*.

As the MRPL is unobserved, I now derive a formula expressing labor market power in terms of observables and describe how labor shares connect to labor output elasticities and product and labor market power. I detail the full derivation in the online Appendix B.1.

I follow De Loecker and Warzynski (2012), who have shown that one can derive a firm's product market power/markup (μ_{it}) from its cost-minimization problem by using a first order condition with respect to a flexible input for which prices are exogenous to firms (intermediates):

$$\mu_{it} = \theta^M_{it} \frac{P_{it} Q_{it}}{z_{it} M_{it}} \ . \tag{3}$$

P_{it} and z_{it} denote the firm's output price and unit costs for intermediate inputs. θ^X_{it} denotes the output elasticity of input $X = \{L, M, K\}$. $\mu_{it} > 1$ indicates that the firm possesses product market power. Reformulating Eq. (2) leads to a similar expression (see online Appendix B.1):

$$\mu_{it} = \theta^L_{it} \frac{P_{it} Q_{it}}{w_{it} L_{it}} \frac{1}{\gamma_{it}}. \tag{4}$$

Eq. (4) looks similar to a standard first order condition for labor from a cost-minimization framework. The key difference is that γ_{it} additionally captures labor market power. Instead of deriving (4) from reformulating Eq. (2), one can alternatively consider a cost-minimization framework extending the De Loecker and Warzynski (2012) framework to allow for labor market power and derive (2) from the first order condition for labor.[15] The online Appendix B.2 provides such a framework.

Combining (3) and (4) gives a measurable expression for labor market power:

$$\gamma_{it} = \frac{MRPL_{it}}{w_{it}} = \frac{\theta^L_{it}}{\theta^M_{it}} \frac{z_{it} M_{it}}{w_{it} L_{it}}, \tag{5}$$

Finally, reformulating Eq. (4) gives:

$$LS_{it} \equiv \frac{w_{it} L_{it}}{P_{it} Q_{it}} = \frac{\theta^L_{it}}{\mu_{it} \gamma_{it}} \ . \tag{6}$$

Eq. (6) implies that a fall in the wage share in sales (LS_{it}) either results from increasing product market power (μ_{it}), increasing labor market power (γ_{it}), or a decreasing labor output elasticity (θ^L_{it}), which reflects the importance of labor in firms' production activities. Within my framework, every factor impacting on firms' labor shares works through one of these three channels. Therefore, reallocation processes and variation in these three parameters explain the entire fall of labor's share in the data.

[14] Mertens (2021) shows that γ_{it} is unbiasedly measured even if jointly i) workers within firms differ in their levels of bargaining power and ii) firms exert different degrees of monopsony power over different worker-groups within their workforce. Any worker-firm-specific labor market power terms will perfectly aggregate to the firm-level labor market power measure used in this study.

[15] The advantage of the approach above is that it conveniently nests worker- and firm-side labor market power into one equation.

Multiplying (6) by the ratio of sales to value-added, $P_{it}Q_{it}/VA_{it} \equiv \kappa_{it}$, defines the value-added labor share:

$$LS_{it}^{VA} \equiv \frac{w_{it}L_{it}}{VA_{it}} = \frac{\theta_{it}^{L}\kappa_{it}}{\mu_{it}\gamma_{it}}, \tag{7}$$

where, under certain conditions, $\theta_{it}^{L}\kappa_{it} = \theta_{it}^{VAL}$ approximates the value-added output elasticity of labor.[16] This shows how changes in firms' value-added depth explain the wedge between the changes of LS_{it}^{VA} and LS_{it} displayed in Fig. 1.

For most of the paper, I focus on the gross output labor share, as it naturally results from the firms' production perspective. Moreover, market power parameters do not necessarily have a theoretical foundation under the value-added concept. For instance, the markup under the value-added concept refers to the value-added price over marginal costs for one unit of value-added and is theoretically related to the price elasticity of demand for value-added. Unless these objects are identical to their gross output counterparts, they are neither part of firms' optimization problems nor of consumers' demand functions. Nevertheless, from an accounting perspective the value-added labor share is informative on the relative importance of labor and capital in firms' production processes and on inequality between suppliers of labor and owners of capital. I therefore replicate key results for the value-added labor share concept in online Appendix F.1.

3.2. Insights from separating market power into labor and product market power

Eqs. (6) and (7) are reminiscent of Hall, 1990 and several recent studies use similar expressions to motivate how rising markups could have contributed to declining labor shares (e.g. De Loecker and Eeckhout, 2020 and DLEU). The key differences between existing work and the framework used here is that I separate firm market power into product and labor market power. From that I assess whether a fall of labor's share coincides with an increase in firms' product or labor market power (or both). Frameworks assuming competitive labor markets abstract from this latter source of firm market power as being a potential driver of falling labor shares.

Moreover, separating firm market power into product and labor market power is informative on the causes of firm market power as it sheds light on whether it results from product or labor markets. In this context, online Appendix B.3 shows that the baseline market power measure in DLEU, denoted by μ_{it}^{DLEU}, is a function of product and labor market power: $\mu_{it}^{DLEU} = ((\theta_{it}^{M} + \theta_{it}^{L})/(\theta_{it}^{M}\gamma_{it} + \theta_{it}^{L}))\mu_{it}\gamma_{it}$.[17]

3.3. The distortion parameter

Under competitive product and labor markets, the wage share equals the aggregate labor output elasticity. I term changes in labor's share corresponding to changes in labor's output elasticity as efficient as they reflect optimal adjustments in firms' production processes that (ceteris paribus) are not accompanied by a reduction of aggregate output. Contrary, I term a fall of labor's share as inefficient if it results from increasing market power because firms with factor or product market power demand too little inputs and produce too little output.

To assess whether the declining wage share is an efficient (decrease in labor's output elasticity) or an inefficient (increase in product or labor market power) outcome, I compare relative changes in the aggregate labor share with relative changes in the aggregate labor output elasticity (using revenue weights for aggregation):

$$\psi_t \equiv \left[\frac{\left(\theta_{t=1995}^{L} - \theta_{t}^{L}\right)}{\theta_{t=1995}^{L}} - \frac{(LS_{t=1995} - LS_{t})}{LS_{t=1995}} \right] 100. \tag{8}$$

$(\theta_{t=1995}^{L} - \theta_{t}^{L})/\theta_{t=1995}^{L}$ measures the counterfactual percentage change in labor's share relative to 1995 had output and input market power been constant. This term reflects the change in labor's share solely due to changes in firms' production processes. ψ_t captures every change in labor's share that cannot be explained by a change in labor's output elasticity, which through the lens of this study's framework refers to changes in product and labor market power. If a falling wage share is caused by a rise of firms' output or labor market power, ψ_t declines over time. If this is not the case, the above framework implies that a declining wage share is an efficient outcome.

3.4. Recovering output elasticities

Before utilizing Eqs. (3), (5), and (8) to study how changes in labor's share relate to changes in the labor output elasticity and product and labor market power, I must estimate a production function to recover firms' output elasticities. Depending on the functional form of the production function, output elasticities vary between firms and across time. For instance, a Cobb-Douglas specification would produce *time-constant* and *industry-specific* output elasticities, which would attribute the

[16] $\theta^{L}{}_{it}\kappa_{it}$ measures labor's value-added output elasticity if at the firm-level $\partial Q_{it}/\partial L_{it} = \partial VA_{it}/\partial L_{it}$. Due to this strong assumption, I treat $\theta^{L}{}_{it}\kappa_{it}$ as an approximation. The online Appendix F.1 applies this approximation to rescale key results to the value-added concept and provides additional discussion.

[17] Under competitive labor markets ($\gamma_{it}=1$) , $\mu^{DLEU}{}_{it}=\mu_{it}$. For the manufacturing sector, DLEU show that their results are robust to using a markup measure based on the materials input decision (i.e. μ_{it}). Still, my analysis highlights the importance of accounting for input market power to understand the causes of changes in firms' total market power.

entire decline in labor's share to rising market power by construction. To avoid this, I apply a translog model, allowing for time- and firm-specific output elasticities:

$$q_{it} = \phi_{it}'\boldsymbol{\beta} + \omega_{it} + \varepsilon_{it}. \tag{9}$$

Lower-case letters denote logs. ϕ_{it} is a vector capturing production inputs and their interactions, $\boldsymbol{\beta}$ is a vector of coefficients, and ε_{it} is an i.i.d. error term.

Productivity, ω_{it}, is Hicks-neutral and can be influenced by firm actions. The firm knows ω_{it} before choosing its consumption of intermediate inputs. Given the characteristics of German factor markets, I assume that the innovation in productivity is uncorrelated with the input decisions for capital and labor.[18] The output elasticity of any input x_{it} is given by $q_{it}/\partial x_{it} = \theta_{it}^{X}$.[19] Changes in θ_{it}^{X} reflect a repositioning of firms on their production function defined by $\boldsymbol{\beta}$.

Due to Hicks-neutrality of ω_{it} and constant parameters $\boldsymbol{\beta}$, the production model specified above cannot account for factor-augmenting technical change that raises the productivity of specific inputs. Output elasticities can, however, still change due to changes in quality-adjusted relative factor prices, which are also affected by factor-specific technological change that is embodied in new production factors (Grossman and Oberfield, 2021). Nevertheless, irrespective of its causes, changes in output elasticities always reflect a change in firms' mode of production, which is the focus of this study. In Section 5, I discuss alternative production models that, among others, allow the parameters $\boldsymbol{\beta}$ to vary over time at the industry level. As noted in DLEU , this also captures industry-level factor-augmenting technological and my results are highly robust to this and other specifications.[20]

To recover unbiased and consistent estimates of firms' production function (9), I need to address three identification issues. First, I do not directly observe ω_{it}. Yet, firms' flexible input decisions (intermediate inputs) depend on ω_{it}, causing a simultaneity problem. Second, I do not observe firm-specific input prices. If input prices are correlated with input choices, estimating (9) without controlling for input price variation across firms causes a bias in the estimated input coefficients. Third, I do not directly observe q_{it} *for multi-product firms* as one cannot aggregate product quantities across firms' various products (liters of beverages vs. kilogram of food). Using revenues deflated by an industry-level deflator to approximate q_{it} is infeasible as this would contaminate my coefficients with an unobserved term related to firms' output price variation. The following subsections describe how I solve these identification issues.

3.4.1. Accounting for firm-specific price variation

To circumvent the problem that q_{it} is not directly observable for multi-product firms, I follow Eslava et al. (2004) in calculating a *firm-specific* price index, π_{it}, from firm-specific product price information. I use this index as a deflator to purge firm revenues (of all firms) from price variation. I detail the calculation of π_{it} in the online Appendix C.4. With slightly abusing notation, I keep using q_{it} for the resulting quasi-quantities.

To control for unobserved firm input prices, I follow DLGKP and formulate a price-control function from firm-product-level price information that I add to the production function (9):

$$q_{it} = \tilde{\phi}_{it}'\boldsymbol{\beta} + B_{it}\Big((\pi_{it},\ ms_{it},\ G_{it},\ D_{it}) \times \phi_{it}^{c}; \boldsymbol{\beta}\Big) + \omega_{it} + \varepsilon_{it}. \tag{10}$$

$B_{it}(.) = B_{it}((\pi_{it},\ ms_{it},\ G_{it},\ D_{it}) \times \phi_{it}^{c}; \boldsymbol{\beta})$ is a price control function consisting of the firm-specific output price index (π_{it}), a weighted average of firms' product market revenue shares (ms_{it}), a headquarter location dummy (G_{it}) and a four-digit industry dummy (D_{it}). $\phi_{it}^{c} = \{1; \tilde{\phi}_{it}\}$ contains two vectors. $\tilde{\phi}_{it}$ includes the same input terms as ϕ_{it}, either in monetary terms and deflated by an industry-level deflator or already reported in quantities (labor). The tilde indicates that some variables in $\tilde{\phi}_{it}$ are not expressed in true quantities (capital and intermediate inputs). The constant entering ϕ_{it}^{c} highlights that elements in $B(.)$ enter the price control function linearly and interacted with $\tilde{\phi}_{it}$ (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 firms' input prices. In particular, I assume that product prices and market shares contain information about product quality and that producing high-quality products demands expensive high-quality inputs. As DLGKP discuss, this motivates to include a price control function containing output price and market share information on the right-hand side of the production function to absorb 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.[21] Although being restrictive, this is a weaker assumption than the one employed in

[18] This is consistent with other studies (DLGKP), with labor and capital inputs facing adjustment frictions but labor being more flexible than capital, and with the strong employment protection laws in Germany (OECD (2018)), which are a potential factor of worker-side labor market power. My results hold when assuming flexible labor (section 5.2).

[19] I define the production function as: $q_{it}=\beta_l l_{it}+\beta_m m_{it}+\beta_{ll} l^2{}_{it}+\beta_{mm} m^2{}_{it}+\beta_{kk} k^2{}_{it}+\beta_{lk} l_{it} k_{it}+\beta_{lm} l_{it} m_{it}+\beta_{km} k_{it} m_{it}+\beta_{lkm} l_{it} k_{it} m_{it}+\omega_{it}+\varepsilon_{it}$.

[20] Under the assumption of exogenous wages to firms, a few recent studies estimate the bias in technological change in a similar way as I estimate labor market power (e.g. Doraszelski & Jaumandreu (2018); Demirer (2020); Raval (2020)). Results and evidence discussed in section 5 support the interpretation of as labor market power.

[21] I thus assume that input prices for intermediates and capital do not depend on input quantities as these inputs enter as deflated input expenditures. Defining labor in terms of expenditures, would demand me to extent this assumption to the labor input, which I want to avoid in my setting because labor market power affects wages.

studies without access to firm-level price information and in which it is assumed that firms face identical input and output prices within industries.

A notable difference between the original approach of DLGKP and the one I apply is that DLGKP estimate product-level production functions, whereas I transfer their framework to the firm-level.[22] 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. This assumes 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 products of a firm. These or even stronger assumptions are always implicitly invoked when estimating firm-level production functions.

Finally, note that even if some of the above assumptions do not hold, including the price control function is still best practice. This is because the price control function 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.[23]

3.4.2. Unobserved productivity and identifying moments

To solve the simultaneity problem from firms' flexible input decision being dependent on firms' productivity, I employ a control function approach in the spirit of Olley and Pakes (1996). This approach derives a control function for productivity from inverting the firm's input demand function for a flexible input. I base my control function on firms' input decision for energy and raw materials, e_{it}, which are components of total intermediate inputs. The inverted demand function for e_{it} can be written as a function $g_{it}(.) = g_{it}(e_{it},\ k_{it},\ l_{it}, \boldsymbol{\nu}_{it}) = \omega_{it}$ that defines productivity and depends on e_{it}, capital, labor, and additional state variables specified in $\boldsymbol{\nu}_{it}$. Ideally, $\boldsymbol{\nu}_{it}$ should capture a broad set of variables affecting demand for e_{it}. In my case, this includes a dummy variable for export activity (Exp_{it}), the logged number of products a firm produces ($Nump_{it}$), and the logged average wage it pays. Including the latter absorbs unobserved quality and price differences that shift demand for e_{it} (De Loecker and Scott, 2016).[24]

I assume that productivity follows a first order Markov process that can be shifted by firm actions, implying the law of motion: $\omega_{it} = h_{it}(\omega_{it-1}, \boldsymbol{\Lambda}_{it-1}) + \xi_{it} = h_{it}(.) + \xi_{it}$. ξ_{it} denotes the innovation in productivity and $\boldsymbol{\Lambda}_{it} = (EX_{it}, NumP_{it})$ reflects that I allow for learning effects from export market participation and (dis)economies of scope to influence productivity. Combining the law of motion for productivity with $g_{it}(.)$ and substituting everything into (10) gives:

$$q_{it} = \tilde{\phi}_{it}'\boldsymbol{\beta} + B_{it}(.) + h_{it}(.) + \xi_{it} + \varepsilon_{it}. \tag{11}$$

I estimate Eq. (11) using a one-step estimator as in Wooldridge (2009).[25] This estimator uses lagged values of flexible inputs as instruments for their contemporary values to address the dependence of firms' flexible input decisions on realizations of ξ_{it}. The identifying moments are given by:

$$E((\varepsilon_{it} + \xi_{it})\Upsilon_{it}) = 0, \tag{12}$$

where Υ_{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 (online Appendix E provides a formal definition of Υ_{it}).

These moments allow for output prices to respond to productivity shocks but demand that they are correlated over time. Contrary, decisions about product mix, location, and exit and entry into export markets are quasi-fixed variables. This captures the existence of sunk costs when entering export markets or building new manufacturing facilities.

I estimate (11) separately for each NACE rev. 1.1 two-digit industry and control for a full set of time dummies. Across all industries, mean (median) output elasticities for capital, labor, and intermediate inputs respectively are 0.11 (0.11), 0.30 (0.31), and 0.64 (0.63). Online Appendix C.2 reports detailed results from the production function estimation.

Having estimated the production function, I calculate firms' product and labor market power using Eqs. (3) and (5).[26] To account for measurement error when calculating μ_{it}, I apply the error correction of De Loecker and Warzynski (2012), i.e. I project output on a polynomial of variables in $\tilde{\phi}_{it}$, $B_{it}(.)$, and $h_{it}(.)$ and use the residuals of this auxiliary regression as a correction factor in Eq. (3) (see De Loecker and Warzynski (2012). To ensure that I can compare aggregate statistics, I only keep firms with information for all components of Eq. (6). The final sample consists of 212,159 firm-year observations, for which online Appendix C.2 summarizes key variables of this article.

[22] Conducting the estimation at the firm-product-level is unsuitable for my study as calculating firm-product-level labor market power demands task-specific wage and employment information that is unavailable to me (online Appendix G provides a discussion).

[23] Including the price control function also helps absorbing unobserved variation in firms' marginal costs, which addresses the critique in Doraszelski & Jaumandreu (2020).

[24] As I base my control function on e_{it}, I do not face the identification issues discussed in Gandhi et al. (2020).

[25] I approximate $h_{it}(.)$ by a third order polynomial in all of its elements, except for the variables in $\boldsymbol{\nu}_{it}$. Those I add linearly. Due to parameter constraints, $B_{it}(.)$ is approximated by a flexible polynomial using an implementation similar to DLGKP where I interact production factors with the output price index and add the market share and industry and location dummies linearly. All results are robust to different specification of both control functions.

[26] To avoid that outliers drive my results, I exclude observations with negative output elasticities and the one percent top and bottom outliers in the distributions of $\theta^L{}_{it}$, $\theta^M{}_{it}$, $\theta^K{}_{it}$, and (LS_{it} - $\theta^L{}_{it}$).

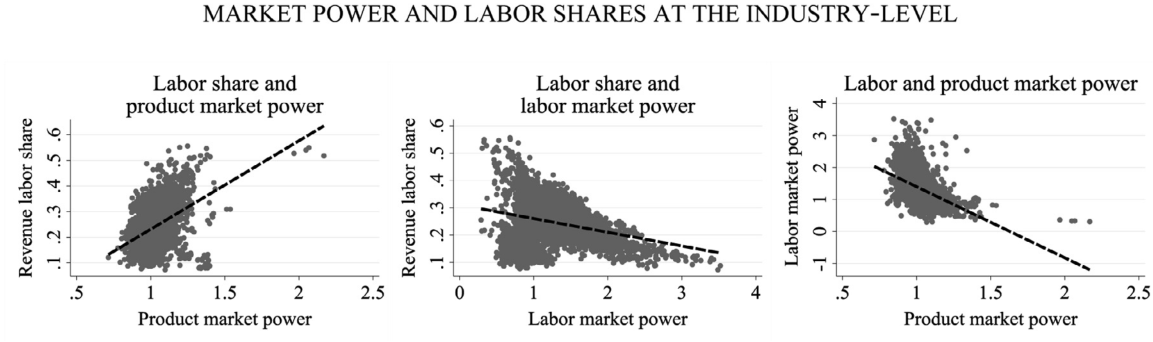

Fig. 2. Correlation between industry-level revenue labor shares, product market power, and labor market power. Four-digit industries with at least three firms. Sales-weighted aggregations of market power parameters. Germany's manufacturing sector. Sample firms.

4. Results

This section presents evidence on the evolution of labor shares, output elasticities, and product and labor market power parameters. Section 4.1 analyzes how product and labor market power relate to firm- and industry-level labor shares. Section 4.2 investigates how my variables of interest change over time. Section 4.3 dissects movements of these variables into within- and between-firm changes. Finally, Section 4.4 discusses the extent to which changes in firms' market power and production processes explain the documented change in labor's share.

4.1. Market power and labor's share

Fig. 2 correlates labor shares with market power parameters at the four-digit industry level. For aggregation I use sales weights for all variables. Alternatively, one can use cost weights to aggregate market power parameters, which I do in online Appendix F.1 (results are unchanged).[27]

Standard theory implies that, under competitive labor markets, product market power will reduce labor demand by reducing firms' output. This causes a reduction in wages on an increasing labor supply curve and reduces labor's share. Yet, Fig. 2 shows that industry-level labor shares are *positively* associated with product market power, but *negatively* correlated with labor market power. The reason for this is a negative relationship between firms' labor and product market power, implying that firms with high product market power share rents with their employees. These rent-sharing processes even overcompensate the negative effect of product market power on labor shares leading to the positive association between labor shares and product markups.[28]

Table 1 shows that this also holds at the firm-level by regressing labor shares on labor output elasticities and market power parameters. Note that I am *only interested in the change in the coefficient on* μ_{it} *after including* γ_{it}. Of course, labor shares are perfectly explained by labor output elasticities and market power parameters. Yet, the change in the coefficient on the product market power parameter is informative on the role of labor market power in linking product market power to labor shares. Table 1 shows that irrespective of whether I rely on cross-sectional or within-firm variation, firms' product market power, μ_{it}, is *positively* correlated with firms' labor shares when I omit the labor market power parameter, γ_{it}. Conditioning on labor market power drastically reduces the coefficient on μ_{it}, turning it negative. Hence, also at the firm-level, firms with higher product market power share rents extensively with their employees, leading to *higher* labor shares within these firms.[29]

My findings are consistent with a rent-sharing model for the German manufacturing sector and demonstrate that an abstraction from labor market imperfections (as often done in the literature) might misguide conclusions on the relationship between product market power and labor shares. The positive association between product market power and labor shares at the firm and industry level is striking given that much of the literature connects product rather than labor market power to declining labor shares.

[27] Depending on the context, one weighting scheme may be preferable over the other. Whereas cost weights produce a more appropriate welfare measure of market power in models using CES aggregators across goods and sectors (Edmond et al. (2018)), sales-weighted measures better capture firm market power associated with the production of a representative bundle of goods – which is typically constructed using sales weights in other contexts (De Loecker and Eeckhout (2018)).

[28] Intuitively, higher firm rents may increase the incentives for workers to bargain for a share of those rents (Nickell (1999)).

[29] These findings raise questions about strategic interactions between product and labor market power. For instance, firms could utilize their monopsony power to enter highly competitive markets while still being profitable. Studying these strategic interactions goes, however, beyond the scope of this study.

Table 1
Labor shares and market power, firm- level analysis.

	Revenue labor share				Value-added labor share			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
θ^L_{it}	0.509***	0.984***	0.760***	0.957***				
	(0.0039)	(0.0017)	(0.0067)	(0.0034)				
θ^{VAL}_{it}					0.435***	1.274***	1.188***	1.408***
					(0.0047)	(0.0024)	(0.0048)	(0.0021)
μ_{it}	1.881***	−0.873***	1.504***	−0.656***	0.849***	−1.156***	1.665***	−0.714***
	(0.0135)	(0.0083)	(0.0180)	(0.00157)	(0.0117)	(0.073)	(0.0198)	(0.0152)
γ_{it}		−0.968***		−0.925***		−1.212***		−1.156***
		(0.0021)		(0.0049)		(0.0027)		(0.0044)
Time FE	NO	NO	YES	YES	NO	NO	YES	YES
Firm-industry FE	NO	NO	YES	YES	NO	NO	YES	YES
Observations	212,159	212,159	206,103	206,103	212,159	212,159	206,103	206,103
R-squared	0.618	0.941	0.950	0.977	0.265	0.925	0.902	0.981
Num. firms	40,778	40,778	35,412	35,412	40,778	40,778	35,412	35,412

Notes: Table 1 reports results from projecting labor shares on market power parameters at the firm level. Column 1–4 show results for the revenue labor share. Column 5–8 show results for the value-added labor share. Standard errors are reported in parentheses and clustered at the firm level. Significance: *10 percent, **5 percent, ***1 percent. The number of firms significantly drops after including fixed effects due to singleton dummies.

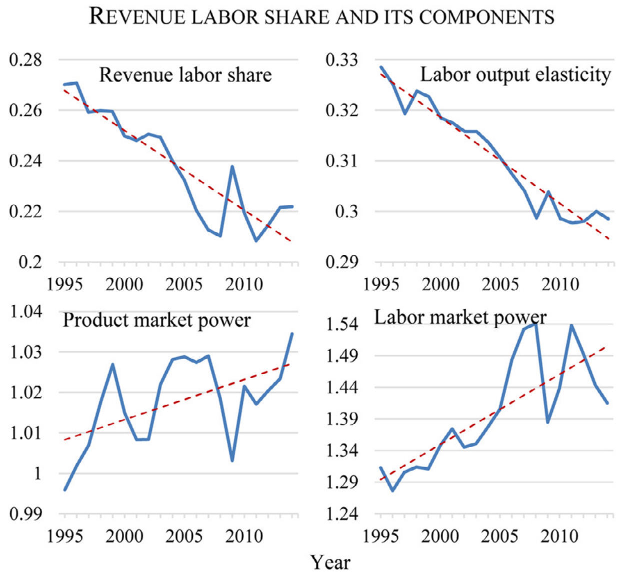

Fig. 3. Aggregates of firm-level labor shares, output elasticities of labor, product market power, and labor market power. Sales-weighted aggregates. Red dashed lines show linear trends. Germany's manufacturing sector. Sample firms.

4.2. Aggregate movements

Fig. 3 displays the evolution of manufacturing sector aggregates of labor shares, product market power, labor market power, and labor output elasticities. Again, I focus on sales-weighted results for all variables and report results using cost-weights for market power parameters in online Appendix F.1 (results are qualitatively unchanged).

The fall of labor's share (from 0.27 to 0.22) jointly coincides with a fall of the output elasticity of labor, a moderate increase in product market power and a strong rise in labor market power. The strong decline of labor's output elasticity (from 0.329 to 0.299) implies that labor became less important in firms production processes in past decades. Online Appendix D investigates more into the evolution of output elasticities and discuss movements of industry-level average and aggregate labor, capital, and intermediate input output elasticities. Across almost all industries, labor output elasticities exhibit clear negative time trends, suggesting that the fall in the aggregate labor output elasticity is not a results of reallocation processes between industries. Although decreasing in most industries, capital output elasticities show an overall weaker decline. Most notably, intermediate input output elasticities show a strong increase. Jointly, this suggests an increasing importance of intermediate inputs in firms' production activities which reallocates value-added factor shares away from labor and towards capital. This is exactly what one would expect from an increasing tendency of German manufacturing sector firms to outsource/offshore labor-intensive tasks, as documented in the literature (Sinn, 2006; Goldschmidt and Schmieder, 2017).

With respect to the market power parameters, I find that whereas firms' labor market power is high and strongly increasing, firms' product market power, although also increasing, stays on comparably low levels. Aggregate product and labor market power respectively rose from 1.00 to 1.03 and from 1.31 to 1.42, i.e. in 2014, wages were 42% below the MRPL. Labor market power is thus the main source of (growing) firm market power in the German manufacturing sector.

The rise of labor market power during the early 2000s coincides with the introduction of Germany's major labor market reforms (the "Hartz-reforms"), which, among others, decreased unemployment benefits and increased the flexibility of labor markets. Moreover, the increase in firms' labor market power coincides with secular falls in the union density and the worker share covered by collectively bargained wage standards over the past decades in Germany (Dustmann et al., 2014; OECD, 2017).

4.3. Between- and within-firm changes

To understand the mechanisms behind the documented changes, I use a within-between-firm decomposition. The aggregate value, x_t, of any variable, x_{it}, can be decomposed as follows:

$$x_t = \sum_i s_{it} x_{it} = \bar{x}_t + cov_t(x_{it}, s_{it}), \tag{14}$$

where s_{it} is the weight of economic importance (sales or costs). $\bar{x}_t$ and $cov_t(x_{it}, s_{it})$ denote the unweighted average of x_{it} across firms and the covariance between x_{it} and s_{it} (Olley and Pakes, 1996).[30] Changes in the unweighted average reflect within-firm changes. Changes in the covariance reflect between-firm changes. Fig. 4 displays this decomposition for aggregates of LS_{it}, θ^L_{it}, μ_{it}, and γ_{it}. Panel A plots unweighted averages (within-firm contribution). Panel B shows covariance terms (between-firm contribution).

The decline in the labor share has a strong within- and between-firm component. For labor's output elasticity, the within-firm component dominates, suggesting that its fall is driven by factors influencing most manufacturing firms similarly (e.g. technological change, outsourcing).[31] This is consistent with evidence in online Appendix D showing a decline in (unweighted) average labor output elasticities for almost all two-digit industries and raises doubts on common production models assuming *time-constant* output elasticities (as most applied Cobb-Douglas specifications).

The between-firm component is negative for the labor share and aggregate product market power, whereas slightly positive for labor's output elasticity and strongly positive for aggregate labor market power. Hence, *large* firms have *lower* labor shares, *less* product market power, *higher* labor output elasticities, and *clearly higher* labor market power compared to small firms.

The covariance term is often interpreted as a reallocation term (e.g. Autor et al., 2020). Yet, besides measuring changes in market shares between firms, it also captures how variables of interest change *within firms* at different parts of the distribution. For instance, if output elasticities fall most for the largest firms, the covariance between labor output elasticities and market shares declines, even if firm market shares stay constant (Decker et al., 2017). Nevertheless, the covariance term is still informative on the importance of the upper parts of the firm sales (size) distribution in driving aggregate changes. Fig. 4 thus indicates that economic activity becomes increasingly concentrated in firms with lower/declining labor shares, a lower/declining technological importance of labor, higher/increasing product market power, and higher/increasing labor market power.

To understand the role of reallocation processes more explicitly, online Appendix J splits firms into different employment and revenue size classes and studies the quantitative differences between small and large firms behind the covariance terms. There are three important results from this analysis: First, there is considerable variation in levels of labor shares, output elasticities and market power parameters between firms' of different size. For instance, in 2014, firms in the largest size class (more than 250 full time equivalents (FTE)) have an average labor market power parameter of 1.32, whereas for firms in the smallest size class (not more than 50 FTE) this value is 0.79. Second, economic activity reallocates towards large firms over time. And third, large firms show the strongest decline in labor shares and output elasticities of labor and the strongest rise in labor mark power (results are similar when defining size by sales).

Consistent with these differences across the firm size distribution, Fig. 4 shows that the unweighted average of the labor market power parameter is much lower than its weighted average (because most firms are small), whereas the covariance between size and labor market power is large and rising.[32] Firm size is thus an important determinant of labor market power and high and increasing aggregate labor market power mostly results from large and increasing shares of economic activity being concentrated in firms with high and rising labor market power.

Table 2 complements Fig. 4 and provides insights on the quantitative importance of between- vs. within-firm changes. For every variable, the first column reports the relative change in its aggregate value. The second and third columns show

[30] I do not use a dynamic decomposition including separate terms for firm entry and exit (as in Melitz & Polanec (2015)) because my data is a representative sample that rotates every 4-5 years and only contains firms with more than 20 employees, i.e. firm entry and exit in the data confounds true entries and exits with sample entry and exit.

[31] The online Appendix F.1 shows this also for the value-added concept, yet with a somewhat larger importance of between-firm changes for the fall in the value-added labor share.

[32] This also holds for using firms' full time equivalents as aggregation weights (online Appendix F.1).

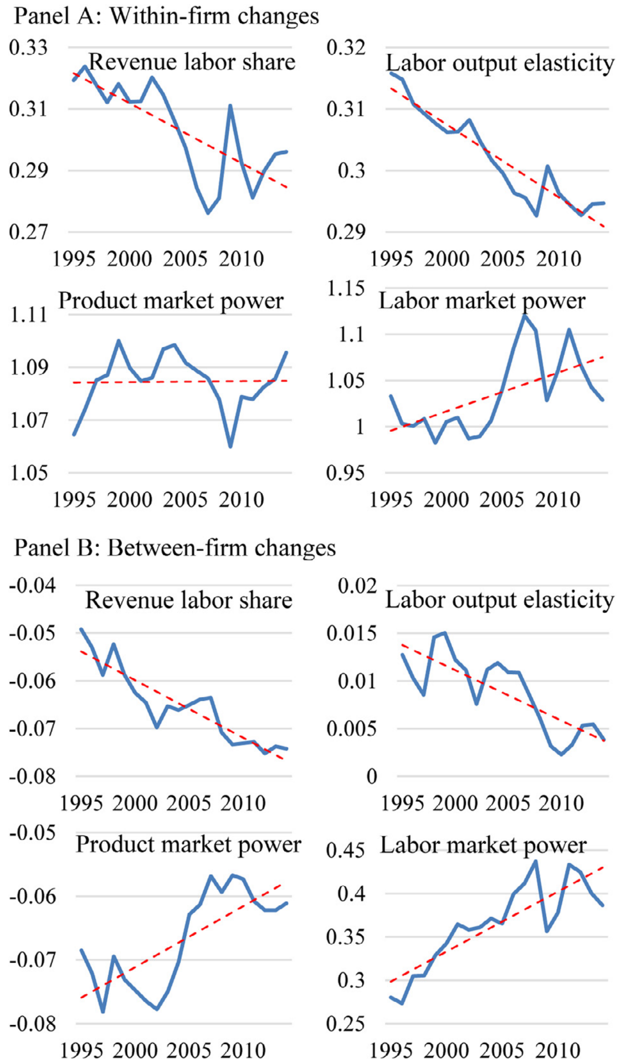

Fig. 4. Aggregates of firm-level labor shares, output elasticities of labor, product market power, and labor market power. Within- and between-firm decomposition. Sales-weighted aggregates. Red dashed lines show linear trends. Germany's manufacturing sector. Sample firms.

Table 2
Relative changes in the aggregate labor share, labor output elasticity, and market power parameters, within- vs. between-firm changes.

	Labor share			Output elasticity of labor		
Period	ΔLS_{jt}	Within contribution	Between contribution	$\Delta\theta^L_{jt}$	Within contribution	Between contribution
1995–2000	−7.50%	−2.58%	−4.92%	−3.07%	−2.91%	−0.16%
2000–2005	−7.00%	−5.98%	−1.02%	−2.50%	−2.09%	−0.41%
2005–2010	−5.54%	−2.10%	−3.45%	−3.84%	−1.06%	−2.78%
2010–2014	+1.10%	+1.62%	−0.52%	−0.02%	−0.54%	+0.52%
1995–2014	−17.85%	−8.59%	−9.25%	−9.14%	−6.43%	−2.71%
	Product market power (rev. weights)			Labor market power (rev. weights)		
Period	$\Delta\mu_{jt}$	Within contribution	Between contribution	$\Delta\gamma_{jt}$	Within contribution	Between contribution
1995–2000	+1.91%	+2.54%	−0.63%	+2.64%	−2.10%	+4.74%
2000–2005	+1.37%	+0.19%	+1.17%	+4.28%	+2.58%	+1.70%
2005–2010	−0.71%	−1.25%	+0.54%	+2.38%	+1.48%	+0.89%
2010–2014	+1.26%	+1.64%	−0.37%	−1.65%	−2.24%	+0.59%
1995–2014	+3.87%	+3.13%	+0.74%	+7.77%	−0.32%	+8.09%

Notes: Table 2 documents the contribution of within- and between-firm changes to changes in the aggregates of labor shares, labor output elasticities, product market power, and labor market power.

Table 3
Contribution of within- and between-industry changes to aggregate changes in labor's share, labor's output elasticity, and firm market power.

	Labor Share	Labor output elasticity	Labor market power	Product market power
Aggregate change	From 0.27 to 0.22	From 0.33 to 0.30	From 1.31 to 1.42	From 1.00 to 1.03
Within-industry contribution	87.60%	133.55%	35.31%	113.16%
Between-industry contribution	12.40%	−33.55%	64.69%	−13.16%

Notes: Table 3 documents the contribution of within- and between-industry changes to changes in the aggregates of labor shares, labor output elasticities, product market power, and labor market power. For each variable, the first row indicates the total change. The second and third row display the percentage contribution of within- and between-industry changes to the aggregate change. A negative values indicates a contribution of that component to the aggregate change in the opposite direction.

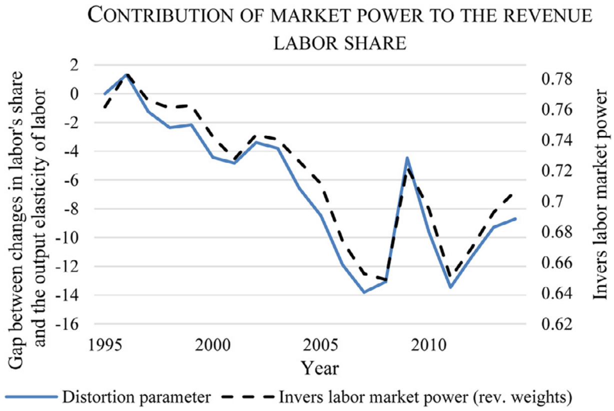

Fig. 5. The contribution of market power to the decline of the revenue labor share and aggregate labor market power. Germany's manufacturing sector. Sample firms.

the within- and between-firm contribution to this change. For instance, the aggregate labor share declined by 8.59% (9.25%) due to within-firm (between-firm) dynamics, showing a similar importance of the within- and between-firm component.

Table 3 displays how cross-industry dynamics affect aggregate changes by showing results from a 2-digit-industry version of the within-between decomposition in Eq. (14). As can be seen, aggregate changes in labor shares, labor output elasticities, and product market power are mainly driven by within-industry changes. For labor market power, I find that within-industry changes account for 35% of the aggregate increase, whereas between-industry changes contribute with 65%.

Finally, online Appendix K provides further insights on within-industry dynamics and conducts the firm-level decomposition exercise for each industry separately. Most industries show changes in labor shares, labor output elasticities, and product market power that are similar to the aggregate changes in these variables. For labor market power, there is, however, large variation across industries, with almost half of them showing declining labor market power. Yet, this is consistent with Table 3 highlighting a particular importance of between-industry changes in explaining increasing labor market power in the German manufacturing sector.

4.4. Rise of market power vs. efficient sources of declining labor shares

Using Eq. (8), Fig. 5 shows how the aggregate wedge (ψ_t) between changes in the labor share and the aggregate output elasticity of labor evolved between 1995 and 2014. The level of ψ_t is depicted on the left vertical axis. The evolution of ψ_t (blue solid line), reflects the percentage change in labor's share due to increasing firm labor and product market power.

Although not visible from Fig. 5, we know from comparing θ_t^L (0.329) and LS_t (0.270) (Fig. 3) that already in 1995, labor shares were below their counter factual level of competitive output and input markets. Over the following decades, the wedge between movements in θ_t^L and LS_t widens. In 2014, ψ_t reaches a value of –8.71, indicating that the labor share fell by 8.71% due to increasing firm market power. As the labor share fell by 17.85%, this implies that increasing product and labor market power account for 49% of the documented decline in the wage share. The remaining 51% are explained by firms moving towards less labor-intensive production processes (labor's output elasticity dropped by 17.85% – 8.71% = 9.14%).

The online Appendix F.1 replicates Fig. 5 for the value-added labor share using the approximation $\theta_{it}^{VAL} = \theta_{it}^{L}\kappa_{it}$ and finds comparable results: the increase (fall) in aggregate market power (the value-added output elasticity of labor) explains 56% (44%) of the declining value-added labor share (see online Appendix F.1 for details). In sum, for both labor share concepts, increasing firm market power and a decreasing technological importance of labor each account for half of the documented decline in labor's share. The is in line with findings for the global labor share based on macroeconomic data (Karabarbounis and Neiman, 2013).

Given that I only find slightly increasing product market power, but strongly rising labor market power levels, my estimates imply that most of the contribution of market power to the decline in labor's share results from increasing firm labor market power.[33] To highlight the key role of rising firm labor market power, the dashed black line in Fig. 5 displays invers values of the aggregate labor market power parameter (levels are represented on the right vertical axis), uncovering a striking similarity between movements in aggregate labor market power and the distortion parameter, ψ_t.

The documented rise of labor market power begs questions about its policy implications and implies room for policies that reduce market distortions and increase labor's share. Guiding policies naturally depends on a variety of aspects. If political decisions makers, however, agree on targeting firms' labor market power, the design of appropriate policies depends on the underlying distribution of market power across firms. In case of Germany's manufacturing sector, labor market power is concentrated in large firms and high and increasing labor market power results from a positive and increasing covariance between firms' share of economic activity and labor market power. Consequently, policies targeting all firms equally or small firms especially are ineffective in reducing aggregate labor market power. A suitable policy to reduce firms' labor market power could therefore extend the existing antitrust law, which currently focuses on preventing excessive product market power, to address the prevalence of market power in labor markets (see also Naidu et al., 2018).

5. Discussion and robustness checks

5.1. Discussion: adjustment costs and labor market power

Labor market power is measured as the wedge between wages and marginal revenue products of labor. Therefore, one concern could be that my labor market power measure captures adjustment frictions *unrelated* to labor market power instead of labor market power. Recap first that adjustment frictions *related* to labor market power (e.g. training costs, unions coordinating labor supply) are a precondition for the existence of worker-side labor market power and should thus enter the labor market power measure I derive. This differs from studies focusing on monopsony power only, which assume that there is no worker-side labor market power (e.g. Hershbein et al., 2019). Moreover, as I focus on *changes* of labor market power, I only require that any unobserved labor adjustment costs *unrelated* to labor market power are not explaining the documented *increase* in labor market power.

As adjustment costs unrelated to labor market power are unobserved, I cannot directly test whether they are a relevant driver of my labor market power measure. Yet, my results provide strong suggestive evidence that the increase in labor market power is not driven by adjustment costs unrelated to labor market power. First, firm labor market power is much higher in large firms (Section 4.3, online Appendix J). Yet, it is well documented that, in Germany, large firms find it much easier than small firms to fill open vacancies (Dettmann et al., 2019). Hence, if adjustment frictions unrelated to labor market power would be a main driver of my labor market power measure, small firms should have higher labor market power than large firms. But the opposite is true. Second, my period of analysis spans several decades of innovations (e.g. broad band internet, online job search engines) and investments in infrastructure (high speed train connections) that reduce information frictions and increase the possibilities of finding suitable worker-firm matches. This should decrease labor adjustment costs. Yet, my labor market power measure strongly rises over these years. Third, Germany experienced large labor market reforms in 2005 (Harz reforms) that increased the flexibility of the labor market and reduced unemployment benefits. This should decrease firms' labor adjustment frictions and increase firms' labor market power. Supporting my interpretation, Fig. 3 shows that my labor market power measure strongly rose after 2005. Finally, in online Appendix H, I correlate my labor market power measure with market concentration and firms being located in regions characterized by a lower union density and smaller share of workers covered by collectively bargained wage agreements (East Germany) and find a highly statistically significant positive association between my labor market power measure and these two proxies for firms' monopsony power and low levels of worker bargaining power. Beyond that, using the same labor market power measure, Dobbelaere, et al. (2020) show that German firms' labor market power, is negatively correlated with the presence of collective bargaining, the presence of work councils, and firm wage premia (wage differences after conditioning on human capital and worker skills) at the firm level.

Overall, these data patterns and findings support my interpretation of increases in γ_{it} as rising labor market power.

5.2. Replication using alternative production models

This section replicates my main results for five alternative production models. Across all these models, I find strong support for my key findings. Whereas I focus on the results in this section, the online Appendices F.2-F.5 present all associated graphs and discuss the individual production models in detail. Table 4 presents an overview on the changes in aggregate measures of labor's output elasticity, firms' product market power and firms' labor market power for all production models I estimated. The results are derived from comparing point estimates of 1995 and 2014 and thus might under- or overstate trends (see online Appendices F.2-F.5).

[33] In my robustness section (5.2), I find that several alternative production models find even small *decreases* in product market power.

Table 4
Changes in aggregates of labor output elasticities, product market power, and labor market power across different production models.

	Baseline (1)	CD-Fix (2)	CD-Flex (3)	TimeCD (4)	TL-Flex (5)	TL-WoP (6)
Output elasticity of labor	0.33 to 0.30 (−0.030)	0.30 to 0.30 (+0.007)	0.28 to 0.28 (+0.003)	0.26 to 0.24 (−0.021)	0.35 to 0.32 (−0.027)	0.28 to 0.24 (−0.040)
Labor market power	1.31 to 1.42 (+0.102)	1.28 to 1.73 (+0.446)	1.22 to 1.62 (+0.397)	1.08 to 1.30 (+0.225)	1.35 to 1.50 (+0.150)	1.00 to 1.04 (+0.034)
Product market power	1.00 to 1.03 (+0.039)	1.02 to 0.97 (−0.048)	1.04 to 0.99 (−0.049)	1.10 to 1.06 (−0.035)	1.01 to 1.05 (+0.039)	1.12 to 1.14 (+0.018)
Market power contribution to declining labor share	49%	112%	105%	54%	57%	22%

Notes: Table 4 reports changes in aggregates of labor output elasticities, product market power, and labor market power across different production models. Column 1 shows results for the baseline specification. Columns 2 and 3 use a Cobb-Douglas specification with time-constant output elasticities, respectively with quasi-fixed and flexible labor inputs. Column 4 shows results for a time-varying Cobb-Douglas specification. Column 5 uses the baseline specification with allowing for flexible labor inputs. Column 6 uses the baseline specification but ignores firm-specific price variation.

Column 1 refers to the baseline specification used in the main text. Columns 2 and 3 start with the simplest possible model: a Cobb-Douglas (CD) production model featuring constant and industry-specific output elasticities. CD-fix assumes quasi-fixed labor inputs, whereas CD-flex assumes flexible labor inputs (i.e. labor responds to productivity shocks). Given constant and industry-specific output elasticities, these models mostly shut down changes in the aggregate labor output elasticity by design. Under these CD specifications, changes in labor's output elasticity can only be caused by a reallocation of market shares between industries or changes in the firm composition. Such changes are small and, if anything, contribute to a slight increase in labor's output elasticity. Thus, by design, both CD models conclude that the increase in market power explains the entire fall in labor's share. The two models are, however, informative on the role of labor as opposed to product market power in explaining falling labor shares: As firms' product market power decreases under these models, they suggest that the entire fall of the wage share results from increasing labor market power. The strong divergence between labor and product market power in these models implies a dramatic reduction in labor compared to intermediate input expenditures over time because output elasticities are held constant in these models.

In column 4, I use a time-varying CD model which produces industry-specific and *time-varying* output elasticities by estimating the production separately for each year.[34] This specification addresses concerns about a functional form dependence between my baseline estimate of labor's output elasticity and labor input levels. A result from such a dependence could be a hard-wired link between movements in labor's share and labor's output elasticity. The time-varying CD model is not subject to this concern. Additionally, the time-varying CD model allows for an limited form of industry-specific factor-augmenting technological change in firms' production processes (DLEU, p.628) . Recent work argues that accounting for factor-augmenting technological change is important when estimating production functions and market power (Doraszelski and Jaumandreu, 2018; Demirer, 2020; Raval, 2020).[35] Yet, a particular issue with approaches to account for factor-augmenting technological change is that they assume exogenous wages to firms, which is unsuitable in my case and rejected by the literature for a plethora of datasets (e.g. Card et al., 2018; Manning, 2021). When allowing for imperfectly competitive labor markets, a time-varying production function specification is therefore the best available robustness check to test for the importance of factor-augmenting technological change in driving my results.[36] Note that, just as my baseline translog production function, the time-varying CD production function does also capture changes in quality-adjusted relative factor prices because this model does not restrict why output elasticities differ between years.

In line with my baseline specification, I find a decrease in labor's output elasticity from the time-varying CD model. Labor market power shows an increase comparable to my baseline model, whereas product market power decreases. Latter implies no role for product market power in contributing to the decline of labor's share. Overall, increasing firm market power and a falling technological importance of labor respectively account for 54% and 46% of the decline in labor's share under a time-varying CD model, which is close to my baseline results. Hence, even when allowing for (industry-specific) factor-augmenting technological change, rising labor market power explains half of the documented decline in labor's share.

[34] As this model demands an enormous parameter space to be estimated, I cannot apply a control function approach to account for the endogeneity of firms' input decisions, yet I apply a reduced from of the input-price control function by controlling for location and four-digit industry dummies (see online Appendix F.3).

[35] Raval (2020) also tests whether markup estimates derived from first order conditions for intermediates and energy expenditures differ and finds significant differences in his data. Mertens (2020, online Appendix), using the same data as in this study here, found that 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 in the German manufacturing sector.

[36] Ideally, I would like to estimate a time-varying translog production function, yet this creates a too large parameter space for an yearly estimation.

Despite the time-varying CD model cannot capture *firm-specific* biased technological change, this finding is reassuring and suggest that the increase in labor market power is not just reflecting unmeasured biased technological change. Otherwise, one should expect at least a small reduction in the relative importance of labor market power.

Nevertheless, this does not imply that technological change does not matter for changes in firms› production processes (firms' labor output elasticities). Technological change can be embodied in new types of inputs and change quality-adjusted relative factor prices (Grossman and Oberfield, 2021). This type of technological change is captured in my translog and the time-varying CD production function and is also emphasized to be a main driver of declining global labor shares in Karabarbounis and Neiman (2013).

The similarity between my baseline and the time-varying Cobb-Douglas specification is also consistent with evidence in Demirer (2020). Although there are several countries where he found a significant difference between a translog production function and a specification allowing for factor-augmenting technological change, he also reported that for some countries differences in parameter estimates where quantitatively small (Demirer, 2020, p. 96).

Column 5 estimates a translog model allowing for labor to respond to productivity shocks, which addresses concerns about my timing assumptions for the labor input. Whereas the estimated changes in the variables of interest are similar to the baseline model, this model estimates a slightly stronger increase in firms' labor market power. Yet, the results are closely in line with my baseline estimates.

Finally, column 6 adds a translog production model where I ignore firm-specific price variation. Due to data constraints, this is also often done in the literature. As discussed, ignoring firm-specific price variation introduces a bias in market power parameters and output elasticities. Ignoring firm price variation i) reduces firm labor market power and moderates its rise, ii) increases product market power, iii) strengthens the fall of labor's output elasticity, and iv) leads to a much larger importance of a falling labor output elasticity in explaining the documented fall in labor's share. Notably, the reported change in labor (product) market power hides a stronger upward (a negative) trend in this measure (see online Appendix F.5).

Given the results in Table 4, I view my baseline model as a conservative benchmark that is supported by the other models. Across all models, I find that i) if I allow for firm- or industry-specific labor output elasticities to vary over time, the aggregate labor output elasticity declines, ii) changes in product market power are small, and iii) the increase in labor marker power dominates the increase in product market power. Moreover, excluding the last model, labor market power levels are clearly above product market power levels. Overall, Table 4 demonstrates that my results on the fall of the aggregate labor output elasticity and the severe increase in aggregate firm labor market power are strong and irrefutable features of the data.

As I further show in online Appendices F.2–5, reoccurring findings across all specifications are that i) the labor output elasticity falls mostly due to within-firm changes, ii) there is a close co-movement between the contribution of market power to the declining labor share and the invers of labor market power, highlighting the key role of labor market power in explaining changes in labor's share, and iii) high and increasing aggregate labor market power results from large firms possessing high labor market power and gaining increasingly higher levels of labor market power and larger market shares.

6. Conclusion

This article sheds light on mechanisms behind declining labor shares. The micro-econometric framework of this article offers three competing explanations for a fall of labor's share: an increase in firms' product market power, an increase in firms' labor market power, or falling labor output elasticities, which reflects a decreasing importance of labor in firms' production activities.

I apply my framework to data on German manufacturing sector firms containing information on firm-specific prices, allowing me to account for firm price variation when estimating output elasticities and market power parameters. Coinciding with the decline of the labor share, I find a high and severely increasing degree of aggregate firm labor market power. In contrast, firms' product market power, although increasing, stays low. Hence, labor market power is the main source of (increasing) firm market power in the German manufacturing sector. Increasing firm market power accounts for one half of the observed decline in the labor share. Given my market power estimates, I conclude that most of this contribution of market power to the declining labor share results from increasing firm labor market power. The remaining half is explained by a declining aggregate labor output elasticity which implies a vital role for changing production processes in explaining the fall of labor's share and which raises doubts on production models featuring constant output elasticities of production factors.

Two important aspects that this article highlights are that large firms possess particularly high labor market power and that most of the rise in aggregate labor market power results from a growth of labor market power in large firms and a reallocation of market shares towards high labor market power firms. Understanding whether such changes are taking place also outside of the German manufacturing sector and, if so, why large firms can capture increasingly large labor market rents and what this implies for the macroeconomy are relevant questions for future research.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.ijindorg.2021.102808.

References

Acemoglu, D., 2003. Labor and capital augmenting technical change. J. Eur. Econ. Assoc. 1 (1), 1–37.
Ashenfelter, O.C., Farber, H., Ransom, M.R., 2010. Labor market monopsony. J. Labor Econ. 28 (2), 203–210.
Autor, D., Dorn, D., Katz, L.F., Patterson, C., Van Reenen, J., 2020. The fall of the labor share and the rise of superstar firms. Q. J. Econ. 135 (2), 645–709.
Azar, J., Marinescu, I., Steinbaum, M., 2020. Labor market concentration. J. Hum. Resour. 1218–9914R1.
Barkai, S., 2020. Declining labor and capital shares. J. Finance 75 (5), 2421–2463.
Berger, D.W., Herkenhoff, K.F., Mongey, S., 2019. Labor market power. Natl. Bureau Econ. Res. (No. w25719).
Blanchard, O., Giavazzi, F., 2003. Macroeconomic effects of regulation and deregulation in goods and labor markets. Q. J. Econ. 118 (3), 879–907.
Bruno, M. (1978). Duality, Intermediate Inputs, and Value-Added. In M. Fuss and D. McFadden (Eds.), Production Economics: A Dual Approach to Theory and Applications (Vol. 2, pp.3-16). Amsterdam: North-Holland.
Brooks, W.J., Kaboski, J.P., Li, Y.A., Qian, W., 2021. Exploitation of Labor? Classical monopsony power and Labor's Share. J. Dev. Econ. 150, 102627.
Card, D., Cardoso, A.R., Heining, J., Kline, P., 2018. Firms and labor market inequality: evidence and some theory. J. Labor Econ. 36 (S1), S13–S70.
Chirinko, R.S., Fazzari, S.M., Meyer, A.P., 2011. A new approach to estimating production function parameters: the elusive capital–labor substitution elasticity. J. Bus. Econom. Statist. 29 (4), 587–594.
Dao, M.C, Das, M.M., Koczan, Z., Lian, W., 2017. Why is labor receiving a smaller share of global income? Theory and empirical evidence. IMF working papers (WP/17/169).
De Loecker, J., Eeckhout, J., 2020. Global market power. Mimeo.
De Loecker, J., Eeckhout, J., 2018. Some thoughts on the debate about (Aggregate) markup measurement. Mimeo.
De Loecker, J., Eeckhout, J., Unger, G., 2020. The rise of market power and the macroeconomic implications. Q. J. Econ. 135 (2), 561–644.
De Loecker, J., Goldberg, P.K., Khandelwal, A.K., Pavcnik, N., 2016. Prices, markups, and trade reform. Econometrica 84 (2), 445–510.
De Loecker, J., Scott, P.T., 2016. Estimating market power Evidence from the US Brewing Industry. Natl. Bureau Econ. Res. (No. w22957).
De Loecker, J., Warzynski, F., 2012. Markups and firm-level export status. Am. Econ. Rev. 102 (6), 2437–2471.
Decker, R.A., Haltiwanger, J., Jarmin, R.S., Miranda, J., 2017. Declining dynamism, allocative efficiency, and the productivity slowdown. Am. Econ. Rev. Paper. Proc. 107 (5), 322–326.
Demirer, M., 2020. Production function estimation with factor-augmenting technology: an application to markups. MIT working paper.
Dettmann, E., Fackler, D., Müller, S., Neuschäffer, G., Slavtchev, V., Leber, U., Schwengler, B, 2019. Fehlende Fachkräfte in Deutschland-Unterschiede in den Betrieben und mögliche Erklärungsfaktoren: ergebnisse aus dem IAB-Betriebspanel 2018. IAB-Forschungsbericht (No. 10/2019).
Diewert, W.E. (1978). Hick's aggregation theorem and the existence of a real value added function. In M. Fuss and D. McFadden (eds.), Production Economics: A Dual Approach to Theory and Applications (Vol. 2, pp.17-51). Amsterdam: North-Holland.
Dobbelaere, S., Mairesse, J., 2013. Panel data estimates of the production function and product and labor market imperfections. J. Appl. Econ. 28 (1), 1–46.
Dixon, R., Lim, G.C., 2020. Is the decline in labour's share in the US driven by changes in technology and/or market power? An empirical analysis. Appl. Econ. 52 (59), 6400–6415.
Dobbelaere, S., Hirsch, B., Müller, S., Neuschaeffer, G, 2020. Organised labour, labour market imperfections, and employer Wage Premia. IZA DP No. 13909.
Doraszelski, U., Jaumandreu, J., 2018. Measuring the bias of technological change. J. Polit. Econ. 126 (3), 1027–1084.
Doraszelski, U., Jaumandreu, J., 2020. The Inconsistency of De Loecker and Warzynski's (2012) Method to Estimate Markups and Some Robust Alternatives. Mimeo.
Dustmann, C., Fitzenberger, B., Schönberg, U., Spitz-Oener, A, 2014. From sick man of Europe to economic superstar: germany's resurgent economy. J. Econ. Perspect. 28 (1), 167–188.
Edmond, C., Midrigan, V., Xu, D.Y., Aniel, Y., 2018. How costly are markups? Natl. Bureau Econ. Res. (No. w24800).
Elsby, M.W., Hobijn, B., Şahin, A., 2013. The decline of the US labor share. Brook. Papers Econ. Activ. 2013 (2), 1–63.
Eslava, M., Haltiwanger, J., Kugler, A., Kugler, M, 2004. The effects of structural reforms on productivity and profitability enhancing reallocation: evidence from Colombia. J. Dev. Econ. 75 (2), 333–371.
Gandhi, A., Navarro, S., Rivers, D., 2020. On the identification of production functions. J. Polit. Econ. 128 (8), 2973–3016.
Garin, A., Silvério, F, 2019. How responsive are wages to demand within the firm? evidence from idiosyncratic export demand shocks. Mimeo.
Giovannoni, O., 2014a. What Do We Know About the Labor Share and the Profit share? Part I: Theories. Working Paper (No. 803). Levy Economics Institute.
Giovannoni, O., 2014b. What Do We Know About the Labor Share and the Profit share? Part II: Empirical studies. Working Paper (No. 804). Levy Economics Institute.
Goldschmidt, D., Schmieder, J.F., 2017. The rise of domestic outsourcing and the evolution of the German wage structure. Q. J. Econ. 132 (3), 1165–1217.
Gouin-Bonenfant, E., 2020. Productivity dispersion, between-firm competition, and the labor share. Mimeo.
Grossman, G.M., Oberfield, E., 2021. The elusive explanation for the declining labor share. Natl. Bureau Econ. Res. (No. w29165).
Hall, R.E., 1990. Invariance Properties of Solow's Productivity Residual. In: Diamond, P. (Ed.), Growth/Productivity/Unemployment: Essays to Celebrate Bob Solow's Birthday. MIT Press, Cambridge & London, pp. 71–112.
Harrison, A., 2005. Has globalization eroded labor's share? Some cross-country evidence. MPRA Paper (No. 39649).
Hershbein, B., Macaluso, C., Yeh, C., 2019. Monopsony in the US labor market. Mimeo.
Kaldor, N., 1955. Alternative theories of distribution. Rev. Econ. Stud. 23 (2), 83–100.
Kaldor, N., 1957. A model of economic growth. Econ. J.l 67 (268), 591–624.
Karabarbounis, L., Neiman, B., 2013. The global decline of the labor share. Q. J. Econ. 129 (1), 61–103.
Kehrig, M., Vincent, N., 2021. Growing productivity without growing wages: the micro-level anatomy of the aggregate labor share decline. Q. J. Econ. 136 (2), 1031–1087.
Keynes, J.M.J.M., 1939. Relative movements of real wages and output. Econ. J. 49 (193), 34–51.
Kline, P., Petkova, N., Williams, H., Zidar, O., 2019. Who profits from patents? rent-sharing at innovative firms. The Quarterly Journal of Economics 134 (3), 1343–1404. doi:10.1093/qje/qjz011.
Koh, D., Santaeulalia-Llopis, R., Zheng, Y, 2020. Labor share decline and intellectual property products capital. Econometrica 88 (6), 2609–2628.
Manning, A., 2021. Monopsony in labor markets: a review. ILR Rev. 74 (1), 3–26.
Mcdonald, I.M., Solow, R.M., 1981. Wage bargaining and employment. Am. Econ. Rev. 71 (5), 896–908.
Mertens, M., 2020. Labor market power and the distorting effects of international trade. Int. J. Ind Organiz. 68, 102562 article.
Mertens, M., 2021. Labour market power and between-firm wage (in) equality Market Power. Mimeo.
Naidu, S., Posner, E.A., Weyl, E.G., 2018. Antitrust Remedies for Labor Market Power. Harv. Law Rev. 132 (2), 536–601.
Nickell, S., 1999. Product markets and labour markets. Labour Econ. 6 (1), 1–20.
Oberfield, E., Raval, D., 2021. Micro data and macro technology. Econometrica 89 (2), 703–732.
OECD, 2017. OECD Employment Outlook 2017. OECD Publishing.
OECD (2018). OECD Indicators of Employment Protection. http://www.oecd.org.

Olley, S., Pakes, A., 1996. The dynamics of productivity in the telecommunications equipment industry. Econometrica 64 (6), 1263–1297.
Raval, D., 2019. The micro elasticity of substitution and non-neutral technology. Rand J. Econ. 50 (1), 147–167.
Raval, D., 2020. Testing the production approach to markup estimation. Mimeo.
Robinson, J., 1933. The Economics of Imperfect Competition. Mac Millan, London.
Sinn, H.W., 2006. The pathological export boom and the bazaar effect: how to solve the German puzzle. World Econ. 29 (9), 1157–1175.
Solow, R.M., 1958. A skeptical note on the constancy of relative shares. Am. Econ. Rev. 48 (4), 618–631.
Wooldridge, J.M., 2009. On estimating firm-level production functions using proxy variables to control for unobservables. Econ. Lett. 104 (3), 112–114.