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The Effects of International Product Market Competition and Demand on Firm Productivity and Labor Market Power

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Introduction

1.1 Background

THE RAPID AND ONGOING PROCESS OF GLOBALIZATION creates profound challenges for firms operating in the market economy. Global integration has increased the size of firms' product markets and the amount of their competitors, while global production networks and dramatically falling transportation costs redefine the nature of firms' production activities. Firms that cannot adapt to this new environment decay and are forced to exit the market, whereas firms that successfully cope with those processes of internationalization prosper and capture markets shares from declining and less productive firms (Pavcnik (2002); Melitz (2003); Melitz & Trefler (2012)).

How firms respond to such changes in their competitive environment has crucial implications for domestic workers, domestic productivity levels, and therefore domestic living standards. In this dissertation I investigate such firm responses for the German manufacturing sector and provide novel causal empirical evidence on how changes in international product market competition and demand affect i) firm-productivity, ii) firms' labor market power, and iii) labor's share in economic output. In all three cases, I analyze the underlying economic mechanisms driving changes in my outcomes of interest. To conduct my analysis, I utilize the unprecedented episode of globalization starting in the late 1990s and recover exogenous variation in firm-specific import competition and export demand from the world markets following a famous approach pioneered by Autor, Dorn, & Hanson (2013).

While I exploit a trade setting to identify how increasing competition and demand affect firms, I argue that the underlying economic mechanisms are fundamental in nature and thus translate also to other scenarios in which firms experience changes in their product market conditions (e.g. entry and exit of competitors or changes in product market regulations).

As will become clear, a key aspect of this dissertation is its focus on accounting for the presence of market power in output and labor markets. Especially latter source of firm market power did not receive much attention in the academic literature so far. Helping to close this gap constitutes one of the main goals of this dissertation.

1.2 Motivating literature

My dissertation builds upon several strands of academic work emerging from the trade, the industrial organization, and the labor market literature. It thus contributes to all those fields from an interdisciplinary perspective. In this section I highlight the connection between the contents covered in this dissertation and the existing literature. As a full coverage of the entire relevant literature would go beyond any scope, I focus on the most recent and inspiring work that motivated much of this dissertation. Where appropriate, the individual chapters provide a more detailed treatment of the literature relevant for the specific topics covered in those chapters.

An important starting point for my dissertation is the recent article by Autor, Dorn, & Hanson (2013), showing the dramatic adverse effects of Chinese import competition on workers in the US. Besides spurring an enormous body of subsequent research on the topic, their paper also provides an appealing framework for analyzing how changes in product market competition and demand causally affect industry- and firm-level outcomes, which I also utilize in this dissertation.[1]

When it comes to debating potential gains from international trade or competition in general, the discussion is often centered around aggregate efficiency gains that could benefit all agents of an economy, if sufficient redistribution would take place (Autor (2018)).[2] In fact, the efficiency enhancing nature of competition is one of the most fundamental tenets in economics.[3] Most of the recent (trade) literature assesses such efficiency enhancing effects based on selection mechanisms: Competition forces inefficient producers out of the market and reallocates market shares towards more efficient firms (see Feenstra (2018a, 2018b) for a review). Although some studies also investigate how firms improve in response to competition (e.g. Aghion, Bloom, Blundell, Griffith, & Howitt (2005), Aghion, Blundell, Griffith, Howitt, & Prantl (2004, 2009)), causal empirical evidence on the conditions and mechanisms leading to within-firm productivity gains through competition is still missing (Holmes & Schmitz (2010)). From a policy perspective, this is, however, important, as political decision makers can influence the degree of competition specific firms face. In this dissertation I address this gap in the literature by providing causal evidence on whether and how firms improve their productivity in response to (import) competition.

A particular problem in the existing literature concerned with estimating firm productivity is that it is typically impossible to separate price effects from true changes in technical efficiency (De Loecker (2011)). This is simply because firms' prices and technical efficiency are usually both unobserved. As I have access to firm-level price information, I can overcome

[1] See Autor, Dorn, & Hanson (2016) for a review of the literature building upon Autor et al. (2013).
[2] Clearly, this only generally holds if redistribution is costless.
[3] See for instance famous work by Hicks (1935), Schumpeter (1942), Stigler (1956), Arrow (1972), and Aghion & Howitt (1998).

this issue and account for the presence of firm-specific price-setting output market power when quantifying firm-level productivity effects of (import) competition.

The presence of market power is not only important for measuring productivity. Variable firm market power may also change aggregate trade gains compared to a standard monopolistic competition model with fixed markups (Feenstra (2018a, 2018b)). As recently shown by De Loecker, Goldberg, Khandelwal, & Pavcnik (2016), firms possessing output market power may only partly pass-through cost savings from cheaper foreign inputs to consumer prices. Extending on this finding, Weinberger (2017) illustrates that heterogeneous output market power levels may allow firms to heterogeneously pass-through productivity gains from cheaper imported intermediate inputs to consumer prices. Through this mechanism, more productive firms can increase their markups relatively more. This reallocates production to the less efficient firms, creating misallocation that reduces aggregate trade gains compared to standard monopolistic competition models.

Given this potential of product market power to create misallocation, it is natural to ask whether competition can function as a disciplining tool for distorted markets and reduce misallocation. Edmond, Midrigan, & Xu (2015) recently investigated this and found that import competition reduces existing misallocation emerging from markup dispersion between firms for plausible model specifications in the case of Taiwan.[4] Similarly, Lu & Yu (2015) showed that trade liberalization reduced markup dispersion in China. Hence, international competition may exert disciplining effects on output markets that reduce misallocation which constitutes an additional margin of gains from trade (and competition). As highlighted by Feenstra (2018a, 2018b), assessing the extent of such widely unstudied pro-(and potentially

[4] Under specific conditions, dispersion in markups may create allocative inefficiencies compared to the first-best scenario because relative prices and relative marginal costs are not aligned. For further details, please see Lerner (1934), Epifani & Gancia (2011), and Edmond et al. (2015).

anti-)competitive effects of (international) competition constitutes an important task for future research.

Motivated by those articles, I investigate in this dissertation whether increasing product market (import) competition and (export) demand may similarly exert disciplining effects or even increase market power distortions on labor markets.[5] As shown in Morlacco (2018), (absolute) levels of input market power distortions reflected in firm-level wedges between marginal costs and marginal products of inputs create market inefficiencies that reduce aggregate output compared to a model with competitive input markets. Hence, by investigating how labor market power levels respond to product market shocks, I shed light on a yet unconsidered margin of pro- (or anti-)competitive gains from trade. This complements the recent literature concerned with assessing pro-competitive effects of trade on product markets that I discussed above.

As the presence of labor market power has also distributional impacts, I further extent my analysis of firm market power and formally connect variation in firms' labor shares to firm market power in output and labor markets. From this setting, I can analyze how increasing (import) competition and (export) demand affect labor's share in economic output through i) within-firm changes in both types of market power and ii) reallocation processes between firms. With that I address a recent strand of academic work investigating how micro-level *product* market power is linked to macro-economic outcomes, as, for instance, falling labor shares (e.g. Barkai (2016); De Loecker, Eeckhout, & Unger (2018); De Loecker & Eeckhout (2018)). In addition, analyzing how the labor share responds to changes in product market competition and demand, complements a large literature strand discussing the role of

[5] To do so I heavily draw from existing work by Dobbelaere & Mairesse (2013). Building upon ideas laid out in De Loecker & Warzynski (2012), Dobbelaere & Mairesse (2013) provide an appealing framework for classifying firms and industries into monopsonistic and efficient bargaining regimes. For further details, I refer to their work and the subsequent research it spurred.

globalization in contributing to falling labor shares. (e.g. Elsby et al. (2013); Karabarbounis & Neiman (2014); Doan & Wan (2017); Gupta & Helble (2018)). Whereas this research strand concentrates on explaining falling labor shares through offshoring activities (i.e. intermediate input imports), I analyze in this dissertation how changes in product market conditions impact on labor's share when output and labor markets are imperfectly competitive.

In IO, research often abstracts from market power in input markets and instead focusses on product market power. Yet, the analysis of labor market power has a long tradition in the labor market literature. For this dissertation, the most relevant and inspiring contributions in this field are those of McDonald & Solow (1981), Manning (2003, 2011), Dobbelaere & Mairesse (2013), and Card, Cardoso, Heining, & Kline (2018). Although there is a recent upspring in interest in modelling monopsonistic input markets in the IO literature, the scenario in which employees instead of firms possess labor market power is rarely subject of interest there (e.g. Azar, Marinescu, Steinbaum, & Taska (2018); Azar & Vives (2018); Morlacco (2018); Azar, Marinescu, & Steinbaum (2019)).[6] This is likely a result of the methodological complexities introduced from jointly allowing for firm and employee side labor market power.[7] As I show in this dissertation, the abstraction from worker bargaining power in the IO literature becomes especially problematic when studying how firms' *output* market power impacts on labor markets (in my case on the labor share). Without worker bargaining power, product market power on the firm side has unambiguously negative effects on labor markets by decreasing labor demand and, eventually through that, wages (as monopolies artificially lower their output quantity to increase prices). In fact, this is exactly

[6] Notable exceptions are recent contribution by Dobbelaere & Vancauteren (2017), Dobbelaere & Kiyota (2018), Kraft (2018), Nesta & Schiavo (2018), and other work building on the approach by Dobbelaere & Mairesse (2013).

[7] For instance, it is difficult to jointly identify the labor supply elasticity and firms' bargaining power from firm-level data. On top of that, it is hard to find suitable instruments for directly measuring the elasticity of the labor supply curve.

the narrative in the current debate on the (potentially negative) effects of rising *product* market power on labor shares, which is based on studies assuming competitive labor markets (e.g. De Loecker, Eeckhout, & Unger (2018); De Loecker & Eeckhout (2018)). Yet, when workers can bargain for a share of firms' product market rents, they may capture parts of those rents in the form of higher wages (and employment).[8] This mechanism makes the effects of product market power on labor markets ambiguous. Incorporating this simple logic into an IO-setting and showing its importance for an analysis of potential mechanisms behind declining labor shares constitutes a main contribution of this dissertation.

1.3 Structure and main results of this dissertation

This dissertation consists of three self-contained articles (chapters 2-4) for which I briefly summarize the main findings in this section. The first one investigates the within-firm productivity effects of import competition from different countries. The second article analyzes how increasing foreign demand and supply impact on firms' labor market power. The third study formally connects the evolution of market power in labor and product markets to the secular decline in labor's share in economic output and investigate how international product market competition and demand, by affecting those two kinds of market power, can account for the fall of the labor share. In the last chapter I provide concluding remarks and discuss future research questions building on the findings of this dissertation.

1.3.1 Import Competition and Firm Productivity: Evidence from Germany*

This study provides novel empirical evidence on the within-firm productivity effects of import competition from high- and low-income countries on German manufacturing sector

[8] For further expositions on this issue I refer the interested reader to Nickell (1999) and Card et al. (2018).

* This chapter is co-authored by Richard Bräuer and Viktor Slavtchev, both from the Halle Institute for Economic Research (Member of the Leibniz Association). Contact: Richard.Braeuer@iwh-halle.de and Viktor.Slavtchev@iwh-halle.de.

firms. By focusing on how firms improve in response to foreign competition, the study complements a large research field on the aggregate productivity gains from trade that instead focusses on reallocation processes. We find positive firm productivity effects only in the case of import competition from high-income countries. In response to import competition from low-income countries surviving firms invest in R&D-activities. This potentially allows firms to become more productive in the longer run but does not immediately lead to productivity gains. The study provides evidence that the positive productivity effects from high-income import competition are a consequence of firms utilizing their existing but unexploited potential to increase productivity. This points to the presence of firm market power in the German manufacturing sector that allows firms to produce below their maximum efficiency level.

1.3.2 Labor Market Power and the Distorting Effects of International Trade

This chapter examines how final product trade shapes labor market imperfections that create market power in labor markets and prevent an efficient market outcome. I develop a framework for measuring such labor market distortions in monetary terms and document large degrees of those distortions in Germany's manufacturing sector. Import competition can only exert labor market disciplining effects when firms rather than workers possess labor market power. Otherwise, increasing foreign demand and import competition tend to fortify existing distortions by amplifying existing labor market power structures. This diminishes trade gains compared to a model with perfectly competitive labor markets.

1.3.3 Micro-Mechanisms behind Declining Labor Shares: Market Power, Production Processes, and Global Competition

Motivated by the second article of this dissertation, this study investigates how changing production processes and increasing market power at the firm level relate to a fall in

Germany's manufacturing sector labor share. Coinciding with the fall of the labor share I document a rise in firms' product and labor market power. I find that in the aggregate imperfectly competitive labor markets are a more relevant source of firm market power than imperfectly competitive product markets. Increasing labor and product market power, however, only account for 30% of the fall in the labor share. The remaining 70% are explained by a transition of firms towards less labor-intensive production activities. When studying the role of final product trade in causing those secular movements, I find that rising foreign export demand contributes to a decline in the labor share by increasing labor market power within firms and by inducing a reallocation of economic activity from non-exporting-high-labor-share to exporting-low-labor-share firms.

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Chapter 2

Import Competition and Firm Productivity: Evidence from Germany

2.1 Introduction

ONE OF THE MOST FUNDAMENTAL TENETS IN ECONOMICS is that competition promotes efficiency.[9] Competitive pressure threatens firms' rents and even their existence. To escape competition, firms take costly actions to improve their productivity (Aw, Roberts & Xu (2011); Aghion, Bloom, Blundell, Griffith, & Howitt (2005); Aghion, Blundell, Griffith, Howitt, & Prantl (2004, 2009). Yet, we know little about the conditions and underlying mechanisms causing increases in firm productivity in response to changes in firms' competitive environment (De Loecker & Goldberg (2014); Shu & Steinwender (2019)).

To shed light on this, we exploit exogenous shocks from the world markets: As foreign industries become more competitive, their firms enter the domestic market (Autor, Dorn, & Hanson (2013)). We study if and how German manufacturing firms increase their productivity in response to such a shock. We find that competition from low-income countries has no direct effect on German firms' productivity. In contrast, competition from other high-income countries incentivizes German firms to improve their productivity. Establishing this so far undocumented empirical finding is our main contribution.

To understand the underlying mechanism of our main result, we investigate how firms adjust when being exposed to different competitors. Irrespective of the country source of import competition, firms experience a drop in revenues and reduce their expenditures for

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[9] E.g. Hicks (1935); Schumpeter (1942); Stigler (1956); Arrow (1972); Aghion & Howitt (1998); Holmes & Schmitz (2010).

production inputs. However, whereas firms respond to high-income import competition by reducing output prices without significantly lowering output quantities, competition from low-income countries causes a fall in sold quantities. While the former explains the increase in physical productivity caused by competition form high-income countries, the latter is likely a result of German firms being unable to compete in terms of prices with product market competition from low-wage countries. Notably, firms surviving competition form low-income countries invest in R&D. This suggests an adjustment strategy aiming at escaping low-income import competition by exploring new markets or inventing more efficient production technologies. In contrast, firms being hit by high-income import competition even decrease their R&D spending, presumably in an attempt to save costs. Overall, we conclude that the productivity enhancing effects of competition we document are not a consequence of increased R&D activities. Instead, they result from releasing existing but unutilized potential to raise efficiency, which brings John Hicks (1935) famous quote to mind: "The best of all monopoly profits is a quiet life."

Firms might be inefficient either because management consumes part of their rents as leisure (Biggerstaff, Cicero & Puckett (2016)) or because of true ignorance about better technology (Bloom & Van Reenen (2010)). New competitors from high-income countries introduce close substitutes to German firms' products into the market. This flattens incumbents' demand curves and makes both behaviors costlier. Our findings provide cross-industry evidence for competition reducing X-inefficiencies, which was previously lacking. We thus supplement studies documenting such competition effects in health care (Bloom, Proper, Seiler & Van Reenen (2015)) or in the oil industry after large world market price shocks (Borenstein & Farrell (2000)).

An important novelty of our study is that we can use firm-product-level price information to back out a quantity-based productivity measure, free from any output price variation. When competition has a negative effect on prices, this is crucial. In that case, projecting a productivity measure containing price variation on import competition underestimates the true effect of import competition on productivity (De Loecker (2011)).

When constructing our import competition measures, we exploit the firm-product dimension of our data to calculate firm-specific competition measures. This allows us to separate the effect of import competition from the effect of intermediate product imports and to account for firms being active in several industries simultaneously. To draw causal inferences, we apply an IV-strategy pioneered by Autor et al. (2013) and instrument trade flows between Germany and its trading partners with trade flows between Germany's trading partners and a set of third countries.

This paper fits into the broad literature on the effects of international trade liberalization. Yet, our focus on the within-firm effects sets our work apart from the majority of this trade literature that instead focuses on productivity gains through selection (Melitz (2003); Bernard, Eaton, Jensen, & Kortum (2003); Melitz & Redding (2013)). Besides this, our study complements recent empirical work investigating how a relaxation of tariffs affects firm performance (e.g. Trefler (2004); Bernard, Jensen, & Schott (2006); Amiti & Konings (2007); Topalova & Khandelwal (2011)). The key difference between our study and this strand of literature is that we focus on true firm-specific import competition rather than on a reduction of industry-wide tariffs. This allows us to clearly identify competition-based effects of international trade.

Additionally, this article relates to theoretical work on firm productivity by Aghion et al. (2005); Aghion et al. (2004, 2009); Impullitti & Licandro (2017). These models build around the idea that a firm's efforts to increase productivity are endogenous to competition. Most closely related, Aghion et al. (2009) show that competition within a specific product segment leads to more innovative activity when the technological distance between competitors is small, such that a successful innovation allows follower firms to leapfrog their competitor. In contrast, when the distance to the competitor becomes larger, the expected rents from innovation decrease, eventually offsetting the incentives to start innovating. As we do not derive a theoretical model and focus on estimating the causal effect of competition on quantity-based productivity, our study complements this strand of literature.

The remainder of the paper is structured as follows. Section 2.2 introduces the data and explains the measurement of our firm-specific import competition measures. Section 2.3 describes our procedure to recover a quantity-based firm-level productivity measure. Section 2.4 covers our econometric strategy to assess the impact of import competition on firm productivity. Section 2.5 presents our empirical results. Section 2.6 concludes.

2.2 Data and measuring import competition

We use administrative yearly panel data on German manufacturing firms with at least 20 employees (AFiD thereafter) for the period 2000-2014. The German Federal Statistical Office and the Statistical Offices of the Länder jointly maintain AFiD, which contains information on firms' production inputs and outputs as well as a variety of further firm characteristics.[10] In principle, AFiD contains the entire universe of firms with at least 20 employees. Yet, to limit the administrative burden, some variables are only collected for a representative subsample encompassing roughly 40% of all firms. Among others, this includes information on intermediate input expenditures and employment by full time equivalents, which we need to

[10] Data source: Research Data Centre of the Federal Statistical Offices of the Statistical Offices Länder. Name of statistics: *"AFiD-Module Produkte", "AFiD-Panel Industriebetriebe", "AFiD-Panel Industrieunternehmen".*

estimate firm TFP. As this subsample is stratified by industry and size-class, which are variables that we observe for all firms, we can construct inverse probability weights to translate all of our results to the underlying firm population.

Notably, AFiD provides detailed information on quantities and factory gate prices for the distinct final products produced by each firm at the nine-digit PRODCOM classification. This information is crucial for our study as i) it allows us to control for firm-specific price variation when estimating firm productivity (see section 2.3) and ii) it enables us to define import competition at the firm level. Calculating import competition at the firm rather than the industry level accounts for firms being active in multiple industries simultaneously and allows us to clearly separate final product competition from competition in firms' supplier markets (i.e. intermediate input imports).

To construct a firm-specific measure for the strength of import competition, we combine the AFiD database with the United Nations Comtrade database (Comtrade thereafter) at the product level. Comtrade contains the value and quantities of products traded between any two countries. After combining this product-level trade data with the product-level production data from AFiD, we calculate firm-level import competition as the revenue weighted share of imports in each firm's product markets:

$$IMP_{it}^{n} = \sum\nolimits_{g} \left[\left(\frac{R_{igt}}{\sum_{g} R_{igt}} \right) \left(\frac{M_{gt}^{n}}{M_{gt}^{World} + \sum_{i} R_{igt}} \right) \right] * 100, \tag{2.1}$$

where g, i, and t respectively indicate the product, firm, and time dimension. M_{gt}^{n} is the value of all German imports of product g from a country(-group) n at time t.[11] $\sum_i R_{igt}$ denotes the total German production value of product g (from firms with at least 20

[11] Excluding exports from the denominator follows Mion & Zhu (2013) and is a consequence of reporting discrepancies between Comtrade and other country-level data sources.

employees), while R_{igt} and $\sum_g R_{igt}$ are a firm's sales of g and total product market revenue, respectively.

We calculate our import competition measure separately for a sample of high-income and low-income countries. Thus, we have: $n = (High, Low)$, where we include USA, Canada, Japan, and South Korea into the high-income group and China, India, Russia, Brazil, South Africa, Argentina, Chile, Mexico, Malaysia, Turkey, Thailand, Tunisia, Bangladesh, Indonesia, Philippines, Vietnam, and Pakistan into the low-income group.[12] We apply this separation because products from high- and low-income countries may differ in their characteristics with respect to product quality, capital-intensity, level of unit costs of production, or embedded technology (e.g. Schott (2004); Hummels & Klenow (2005)). Differentiating imports according to source countries, thus, allows that incentives of firms to improve their efficiency depend on the type of competition they face (e.g. quality vs. price competition). We discuss this further in our results section.

2.3 Estimating firm productivity

To recover a quantity-based measure of firm productivity (i.e. TFPQ), we define the following physical Cobb-Douglas production model:

[12] We excluded countries with negligible shares of Germany's total manufacturing sector imports from our analysis (e.g. Afghanistan). To be conservative, we also excluded European countries because German firms are engaged in extensive transnational production networks within European multicorporate enterprises. Moreover, we excluded some more countries from the high-income group as we need a set of high-income countries for our IV-strategy (see below). Overall, we believe that the countries included represent the respective groups well, so that we do not compromise the generalizability of our results.

(2.2)
$$Q_{it} = L_{it}^{\beta^l} K_{it}^{\beta^k} M_{it}^{\beta^m} e^{\omega_{it}},$$

where Q_{it} denotes produced quantity and L_{it}, K_{it}, and M_{it} respectively are the amount of labor, capital, and intermediates used in the production of Q_{it}.[13] ω_{it} denotes Hicks-neutral total factor productivity. The firm knows ω_{it} before choosing its consumption of intermediate inputs. However, given the characteristics of Germany's factor markets, we assume that the input decisions for capital and labor are uncorrelated with the innovation in firm productivity.[14] Taking logs from (2.2) motivates the following empirical production function:

(2.3)
$$q_{it} = \beta^l l_{it} + \beta^k k_{it} + \beta^m m_{it} + \omega_{it} + \varepsilon_{it},$$

where smaller letters denote logs and ε_{it} enters as an i.i.d. error term. We aim to calculate ω_{it} as a residual after estimating the production function (2.3). Before doing so, however, we need to address three econometric challenges. First, due to differences in physical reporting units across products (e.g. volume vs. kilogram), we cannot define a quantity-based output measure for multi-product firms. To address this issue, we follow Eslava, Haltiwanger, Kugler, & Kugler (2004) and purge observed firm revenue from price variation by deflating it with a firm-specific price index calculated from information on product prices given in our data.[15] With slightly abusing notation, we keep using q_{it} for the resulting quasi-quantities.

Second, although, we observe labor inputs directly in quantities (i.e. in full time equivalents), capital and intermediate inputs are, by their nature, only reported in monetary units. Hence, after deflating k_{it} and m_{it} with industry-j-specific price indices, two

[13] See Appendix A.3 for the construction of the capital series.
[14] Those timing assumptions are consistent with allowing for labor being more flexible than capital. Given the high degree of employment protection in Germany, it is reasonable to define labor as a quasi-fixed input (OECD (2018)).
[15] Appendix A.2 details the construction of this index.

unobserved terms capturing firm-specific deviations from industry-level prices enter our physical production model. Formally:

$$q_{it} = \beta^l l_{it} + \beta^k (k_{it} + p_{it}^k - \bar{p}_{jt}^k) + \beta^m (m_{it} + p_{it}^m - \bar{p}_{jt}^m) + \omega_{it} + \varepsilon_{it},$$

(2.4) $$q_{it} = \beta^l l_{it} + \beta^k \tilde{k}_{it} + \beta^m \widetilde{m}_{it} + \omega_{it} + \varepsilon_{it},$$

where we defined $\tilde{x}_{it} = (x_{it} + p_{it}^x - \bar{p}_{jt}^x)$ for $x = \{k, m\}$, with the tilde indicating that the respective variable is deflated by an industry-level deflator. p_{it}^k and p_{it}^m respectively denote firm-level prices for capital and intermediate inputs and $\bar{p}_{jt}^k$ and $\bar{p}_{jt}^m$ refer to the associated industry-level price indices. As input prices are correlated with output volumes, estimating the above production function without observing p_{it}^k and p_{it}^m produces biased input coefficients (Van Beveren (2012)). To address this input price bias, we follow De Loecker, Goldberg, Khandelwal, & Pavcnik (2016) and assume i) that differences in input prices across firms emerge from quality differences ii) that firms who manufacture high quality outputs do so by using high quality inputs, iii) complementarity in input quality (i.e. firms combine high quality labor with high quality intermediates and capital), and iv) a vertical differentiation model of consumer demand. As discussed in De Loecker et al. (2016), those assumptions allow us to control for input price variation across firms using solely information on output prices. Specifically, for every firm we construct a revenue weighted average of the firm's product price deviations from the industry-wide average product prices for its various products. We denote this index by π_{it} and include it as an additional control variable into our production model:

(2.5) $$q_{it} = \beta^l l_{it} + \beta^k \tilde{k}_{it} + \beta^m \widetilde{m}_{it} + \gamma \pi_{it} + \omega_{it} + \varepsilon_{it}.$$

The last econometric issue we face is that ω_{it} is unobserved but correlated with firms' input decision for flexible production inputs, i.e. with firms' input decision for intermediates.

To solve this issue, we apply a control function approach in the spirit of Olley & Pakes (1996) and Levinsohn & Petrin (2003), where we derive an expression for ω_{it} from inverting firms' demand function for energy and raw materials (which are components of total intermediates), denoted by e_{it}:

$$\omega_{it} = g_{it}(.) = g_{it}(\tilde{k}_{it}, l_{it}, \tilde{e}_{it}, \boldsymbol{z}_{it}). \quad (2.6)$$

$\boldsymbol{z}_{it}$ captures state variables of the firm, which, in addition to capital and labor, influence demand for e_{it} and firm productivity.[16] As noted by De Loecker et al. (2016), $\boldsymbol{z}_{it}$ should be specified as broadly as possible. Therefore, we include dummy variables for export as well as research and development activities, dummy variables for the firm's headquarter and its main four-digit industry, the number of products a firm produces, and firm-level import competition (as defined in section 2.2) into $\boldsymbol{z}_{it}$.[17] Assuming that ω_{it} follows a Markov-process, i.e. $\omega_{it} = \omega_{it-t} + \xi_{it}$, where ξ_{it} denotes the innovation in productivity, and plugging equation (2.6) into (2.5) gives:

$$q_{it} = \beta^l l_{it} + \beta^k \tilde{k}_{it} + \beta^m \widetilde{m}_{it} + \gamma \pi_{it} + g_{it-1}(.) + \xi_{it} + \varepsilon_{it}, \quad (2.7)$$

which constitutes the basis of our estimation. We estimate equation (2.7) in one step following Wooldridge (2009) and instrument $\widetilde{m}_{it}$ and π_{it} with their lags to allow for productivity shocks to affect those flexible variables. Hence, the identifying moments are given by:

$$E\left(\xi_{it} + \varepsilon_{it} | l_{it}, \tilde{k}_{it}, \widetilde{m}_{it-1}, l_{it-1}, \tilde{k}_{it-1}, \tilde{e}_{it-1}, \boldsymbol{z}_{it-1}, \boldsymbol{\Gamma}_{it-1}, \pi_{it-1}\right) = 0, \quad (2.8)$$

[16] To invert firms' demand function for e_{it}, e_{it} must monotonically increase in ω_{it}. This is a widely applied assumption in the literature (e.g. Levinsohn & Petrin (2003); Wooldridge (2009); De Loecker et al. (2016); Petrin & Levinsohn (2012); Petrin & Sivadasan (2013)).

[17] We approximate $g_{it}(.)$ with a third order polynomial in k_{it}, l_{it}, and e_{it} and add variables in $\boldsymbol{z}_{it}$ linearly.

where $\mathbf{\Gamma}_{it}$ collects interaction terms entering $g_{it}(.)$. Having estimated the production function, we recover firm productivity by:

$$\omega_{it} = q_{it} - (\beta^l l_{it} + \beta^k \tilde{k}_{it} + \beta^m \tilde{m}_{it} + \gamma \pi_{it}). \tag{2.9}$$

To allow for differences in production technologies across sectors, we estimate (2.7) separately for every NACE rev. 1.1 two-digit industry with at least 500 observations. Table 2.1 presents the associated results.

Overall, our estimates look reasonable with returns to scale being mostly close to one. Output elasticities vary considerably across industries, highlighting the importance of allowing for differences in production technologies across industries. Note that output elasticities for capital are less precisely estimated than output elasticities for intermediates and labor, which is in line with existing work (e.g. De Loecker et al. (2016); Dhyne, Petrin, Smeets, & Warzynski (2017)). For industries 27, 29, and 35 we even estimate negative values for capital's output elasticity. As such estimates are inconsistent with our production model, we exclude those sectors from our further analysis.[18]

[18] Appendix A.1 provides summary statistics for our final sample of firms.

TABLE 2.1

OUTPUT ELASTICITIES,
BY SECTOR

Sector	Number of observations (1)	Intermediate inputs (2)	Labor (3)	Capital (4)	Returns to scale (5)
15 Food products and beverages	16,576	0.68*** (0.02)	0.22*** (0.02)	0.16*** (0.04)	1.06
17 Textiles	3,917	0.76*** (0.03)	0.25*** (0.04)	0.01 (0.04)	1.05
18 Apparel, dressing, and dyeing of fur	1,366	0.77*** (0.03)	0.18*** (0.04)	0.04 (0.05)	0.99
19 Leather and leather products	774	0.75*** (0.04)	0.21*** (0.05)	0.11 (0.09)	1.07
20 Wood and wood products	2,845	0.70*** (0.03)	0.25*** (0.04)	0.01 (0.05)	0.96
21 Pulp, paper, and paper products	3,614	0.81*** (0.03)	0.18*** (0.04)	0.03 (0.02)	1.02
24 Chemicals and chemical products	7,005	0.76*** (0.02)	0.22*** (0.04)	0.06 (0.04)	1.04
25 Rubber and plastic products	7,810	0.69*** (0.03)	0.10 (0.08)	0.04 (0.03)	0.83
26 Other non-metallic mineral products	6,735	0.74*** (0.02)	0.26*** (0.03)	0.01 (0.03)	1.01
27 Basic metals	5,205	0.72*** (0.03)	0.27*** (0.04)	-0.01 (0.03)	0.98
28 Fabricated metal products	12,915	0.70*** (0.02)	0.29*** (0.05)	0.07** (0.03)	1.06
29 Machinery and equipment	14,444	0.73*** (0.02)	0.13*** (0.04)	-0.04 (0.04)	0.82
30 Electrical and optical equipment	622	0.81*** (0.09)	0.23*** (0.09)	0.28** (0.13)	1.32
31 Electrical machinery and apparatus	5,368	0.68*** (0.03)	0.26*** (0.04)	0.11*** (0.04)	1.05
32 Radio, television, and communication	1,232	0.77*** (0.05)	0.04 (0.11)	0.11 (0.12)	0.92
33 Medical and precision instruments	3,228	0.62*** (0.03)	0.23*** (0.05)	0.11 (0.08)	0.96
34 Motor vehicles and trailers	2,845	0.81*** (0.07)	0.15*** (0.05)	0.05 (0.06)	1.01
35 Transport equipment	778	0.74*** (0.06)	0.12 (0.08)	-0.29** (0.12)	0.57
36 Furniture manufacturing	4,267	0.75*** (0.03)	0.17*** (0.05)	0.04 (0.04)	0.96

Notes: Table 2.1 reports output elasticities for labor, capital, intermediate inputs obtained from estimating the production function (2.7) for every NACE rev. 1.1 two-digit industry with at least 500 observations. Column 1 reports the number of observations used in the estimation of (2.7). Columns 2-4 respectively report output elasticities for intermediate, labor, and capital inputs. Column 5 shows the returns to scale, defined as the sum of the point estimates for the output elasticities. All regressions control for time dummies and are weighted using inverse probability weights. Standard errors are clustered at the firm level and reported in parentheses. Significance: *10 percent, **5 percent, ***1 percent.

Table 2.2 shows estimates of our quantity-based productivity measure, to which we refer as TFPQ, next to a productivity measure that ignores price variation across firms within industries, which we call TFPR. To estimate TFPR, we deflated firm revenues with an industry-level deflator and omitted π_{it} from equations (2.7)-(2.9).[19] While we find only minor differences between our TFPQ and TFPR measures in some sectors (e.g. industries 18, 24, and 31), other industries display huge discrepancies between both productivity measures (e.g. industry 30, 33, and 34). Note that the dispersion in TFPR is smaller than in TFPQ, which is in line with findings in Foster et al. (2008).

TABLE 2.2

FIRM PRODUCTIVITY:
ACCOUNTING VS. NOT ACCOUNTING FOR FIRM PRICE VARIATION

	TFPQ		TFPR	
	Mean	SD	Mean	SD
Sector	(1)	(2)	(3)	(4)
15 Food products and beverages	2.20	0.23	2.83	0.16
17 Textiles	2.97	0.21	3.22	0.14
18 Apparel, dressing, and dyeing of fur	2.62	0.18	2.54	0.13
19 Leather and leather products	1.73	0.19	2.50	0.12
20 Wood and wood products	3.98	0.22	3.24	0.12
21 Pulp, paper, and paper products	2.18	0.20	2.99	0.12
24 Chemicals and chemical products	2.41	0.24	2.50	0.15
25 Rubber and plastic products	4.38	0.32	3.73	0.13
26 Other non-metallic mineral products	3.25	0.23	3.41	0.14
28 Fabricated metal products	2.83	0.26	3.25	0.14
30 Electrical and optical equipment	-1.91	0.54	0.74	0.42
31 Electrical machinery and apparatus	2.71	0.27	2.67	0.17
32 Radio, television, and communication	2.29	0.31	2.37	0.23
33 Medical and precision instruments	3.83	0.27	5.83	0.29
34 Motor vehicles and trailers	2.07	0.21	3.27	0.15
36 Furniture manufacturing	3.06	0.24	2.66	0.16

Notes: Table 2.2 reports firm productivity estimates. Columns 1 and 2 refer to a quantity-based TFP measures, whereas columns 3 and 4 report statistics for a TFP measure that abstracts from firm-level price variation when estimating the production function. Columns 1 and 3 report means. Columns 2 and 4 report standard deviations.

[19] This follows the conceptualization of Foster, Haltiwanger, & Syverson (2008). Strictly speaking, however, if prices vary across firms within industries, our TFPR measure is not a perfect measure of revenue productivity. This is because unobserved firm price variation introduces a bias in the estimated output elasticities of a production model that regresses deflated revenues on deflated input expenditures (when the respective deflators are defined at the industry level (see the discussion above)). In that case, it does not hold that: $TFPR_{it}/P_{it}^{Q} = TFPQ_{it}$, with P_{it}^{Q} denoting a firm's output price. Given that our TFPR measure is the TFP measure widely used in the literature, we believe that the comparison in Table 2.2 is still interesting.

2.5 Identifying the productivity effects of import competition

To assess the effect of import competition on firm productivity, we estimate a fixed-effects model:

$$\omega_{it} = \beta^{High} IMP_{it-1}^{High} + \beta^{Low} IMP_{it-1}^{Low} + \boldsymbol{C}'_{it-1}\gamma + \vartheta_t + \vartheta_{ij}, \quad (2.10)$$

where $\boldsymbol{C}'_{it}$ is a vector of control variables capturing firms' export intensity and number of products. ϑ_t and ϑ_{ij} are time and firm times industry fixed effects, respectively. Controlling for firm times industry fixed effects eliminates the potential for statistical jumps in firm productivity due to changes in firms' industry classification (as the parameters of the production function are estimated separately for individual industries). We thus identify our coefficients using within-firm-within-sector variation. In essence, our regression model is similar to a first difference model but avoids a disproportional loss of observations when working with a rotating panel (as in our case). We weight all observations using inverse probability weights to achieve a representative estimate and lag our import competition variables to allow for a time span of adjustment that is consistent with our production model.

Note that estimating equation (2.10) by OLS might suffer from an endogeneity problem, prohibiting any causal interpretation of our results. Our two main concerns are i) that foreign competitors might specifically target unproductive firms and sectors, reversing causality, and ii) that domestic governments might protect specific sectors and firms from foreign competition.

To solve this endogeneity problem, we apply an instrumental variable strategy following Autor et al. (2013) and Dauth et al. (2014). Specially, we exploit that an increase in the competitiveness of a country-group *n* induces supply shocks also for other countries besides Germany. Using trade flows between German competitors and third countries therefore offers us an exogenous source of variation that is unrelated to specific German policy changes or the particular weakness of German firms. To implement the IV-strategy, we instrument our import competition measures with the share of country-group n's imports in total imports of product g observed in *third* countries. Hence, we define firm-level instruments for country-group $n's$ import competition as:

$$IS_{it}^{n\rightarrow third} = \sum_g \left[\left(\frac{R_{igt}}{\sum_g R_{igt}}\right)\left(\frac{M_{gt}^{n\rightarrow third}}{M_{gt}^{World\rightarrow third}}\right)\right] * 100, \tag{2.11}$$

where $M_{gt}^{n\rightarrow third}$ is the value of product g imports flowing from *n* to *third* countries. As for our endogenous import competition measure, we aggregate product-level trade flows for our instruments to the firm level by using revenue weights.

A crucial point for our IV-strategy to work is that there are no other unobserved confounding factors that are correlated between Germany and countries included in the instrument country-group (e.g. correlated demand and supply shocks or monetary policy within the European Monetary Union). This would violate our exclusion restriction. Besides that, our instruments must be relevant enough to avoid a weak instrument problem. Therefore, we follow Dauth et al. (2014) and include countries with an income level similar to Germany in our instrument country-group, expect for all direct neighbors of Germany and members of the European Monetary Union. Ultimately, our *third* country-group consists of Norway, New Zealand, Israel, Australia, Great Britain, Sweden, and Singapore.[20]

Note that the weighting scheme we use to aggregate product-level trade flows to the firm-level might introduce another endogeneity problem when firms adjust their product-mix in anticipation of foreign competition. In a robustness check shown below we therefore use a more rigorous specification where we base our aggregation of product trade flows for our instruments on constant weights using firms' first observed product portfolio (the product-

[20] Our results are robust to different definitions of the instrument country group.

level data already starts in 1995). This eliminates the potential for any endogenous product mix adjustment by firms.

2.6 Results

2.6.1 Import competition and firm TFP

Table 2.3 shows results from estimating equation (2.10) by OLS and IV.[21] Given that OLS might suffer from an endogeneity problem, we focus our interpretations on the IV-results. For a first overview, we pool import competition from all countries. We find that a one percentage point increase in total import competition causes an increase in firm productivity by 0.2%.[22]

TABLE 2.3

FIRM PRODUCTIVITY AND IMPORT COMPETITION

	OLS	IV
	ω_{it}	ω_{it}
	(1)	(2)
$IMP_{it-1}^{High+Low}$	-0.0001	0.0018***
	(0.0004)	(0.0001)
Firm Controls	YES	YES
Firm $*$ industry FE	YES	YES
Time FE	YES	YES
Observations	78,414	78,414
R-squared	0.986	0.986
First-stage F-test	-	142.00
Number of firms	16,925	16,925

Notes: Table 2.3 reports results from estimating equation (2.10) by OLS (column 1) and IV column (2) when pooling import competition from high- and low-income countries. All regressions are weighted using inverse probability weights and include controls for firms' export intensity and number of products. Standard errors are clustered at the firm level. Significance: *10 percent, **5 percent, ***1 percent.

As several theories suggest that firms' reactions to competition depend on the characteristics of their competitors (i.e. the type of competition they face), Table 2.4 separates total import competition into import competition from high- and low-income countries (as

[21] We report first stage regression for our baseline specification in Appendix A.4.

[22] The downward bias in the OLS-coefficients is consistent with foreign competitors targeting especially unproductive domestic firms.

described by equation (2.10)).[23] The intuition behind this specification is that from a German firm's point of view, import competition from a low-wage country (as China) may pose a completely different threat than import competition from a high-wage country (as the US). This is because compared to Germany, goods from low-income countries are typically characterized by lower unit costs of production and lower quality levels (Schott (2004); Hummels & Klenow (2005)).

The OLS estimator is again inconclusive (column 1). Using our IV-specification, we find that the positive effect of import competition is solely driven by high-income countries (column 2).

TABLE 2.4

FIRM PRODUCTIVITY AND IMPORT COMPETITION,
SEPARATELY FOR IMPORT COMPETITION FROM HIGH- AND LOW-INCOME COUNTRIES

	OLS	IV	IV	IV
	ω_{it}	ω_{it}	ω_{it}	ω_{it}
	(1)	(2)	(3)	(4)
IMP_{it-1}^{High}	0.0004	0.0112***	0.0222***	0.0206**
	(0.0009)	(0.0037)	(0.00713)	(0.0104)
IMP_{it-1}^{Low}	-0.0003	-0.0005	-0.0008	0.0001
	(0.0005)	(0.0010)	(0.00148)	(0.0018)
Firm ∗ industry FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
First portfolios	NO	NO	YES	NO
Single-product firms	NO	NO	NO	YES
Observations	78,414	78,414	73,212	22,729
R-squared	0.986	0.985	0.984	0.982
First-stage F-test	-	36.89	13.13	12.09
Number of firms	16,925	16,925	15,853	5,467

Notes: Table 2.4 reports results from estimating equation (2.10) by OLS and IV when separating import competition into high- and low-income country import competition. Columns 1 and 2 respectively show OLS- and IV-results from our baseline specification using all available firms. Column 3 uses firms first observed product mix to aggregate product-level trade flows to the firm level for the instrument variables. Column 4 runs our baseline specification exclusively for single-product firms. All regressions are weighted using inverse probability weights and include controls for firms' export intensity and number of products. Standard errors are clustered at the firm level. Significance: *10 percent, **5 percent, ***1 percent.

[23] See for instance the literature on North-South trade models (e.g. Grieben & Şener (2009); Khandelwal (2010)) or recent models by Aghion et al. (2005) and Aghion et al. (2004, 2009) where firm innovation depends on the type/intensity of competition firms face.

There are two threats to the IV identification used in column 2. The first threat is that firms anticipate changes in competition and adjust their product portfolio prior to the shock. Thus, firms might self-select into treatment by dropping or entering exposed markets. As discussed in section 2.4, we construct our instrument using firms' first observed product portfolio to alleviate this concern. Column 3 shows that the measured effects are even stronger when accounting for this potential problem.

The second threat is that different countries might attack different parts of firms' product portfolio. If low-income countries only attack firms' peripheral products, we might not measure a response because firms do not care about these products, independent of who competes with them. We gauge the scope of this problem by estimating equation (2.10) for single-product firms only (column 4). We still find that high-income countries are solely responsible for productivity gains.[24]

As accounting for both potential identification problems leads to higher point estimates, we view our main specification as a conservative baseline.

2.6.2 Import competition and firm adjustments

To better understand the strikingly different effects of competition from different country groups, we study the adjustments strategies of firms. Specifically, we analyze the effects of import competition on firms' sales, quantities, prices, input decisions, and R&D expenditures. Table 2.4 reports the associated results, where $\tilde{r}_{it}$, P_{it}, q_{it}, l_{it}, w_{it}, $\tilde{k}_{it}$, $\widetilde{m}_{it}$, and $r\&d_{it}$ respectively refer to the firm's revenue, output price index, quasi-quantities, full-time equivalents, wage bill, capital stock, intermediate expenditures, and R&D expenditures.

[24] We also replicate this with a more elaborate procedure where we estimate the effect of competitive pressure separately for products with different revenue ranks in firms' product portfolio. We again exclusively find positive productivity effects from high-income import competition (results are available on request).

Again, smaller letters denote logs.[25] Note that we focus on the intensive margin of R&D spending by using logged R&D expenditures as dependent variable.[26]

Regardless of its origin, we find that foreign competition affects firm sales negatively (column 1). This assures us that firms are adversely affected by our competition measures. In case of high-income import competition, the reduction in sales is driven by a fall in output prices, whereas firms being hit by low-income import competition reduce their produced quantities. Evidently, firms join into a fierce price competition over market shares with competitors from high-income countries, while they simply resign market shares to low-income competitors.

Next, we analyze how firms adjust their input decisions (columns 4, 5, 6, and 7). Low-income import competition causes firms to reduce their employment and input expenditures. Although firms exposed to high-income import competition also decrease their input expenditures, they do not reduce their employment levels. This discrepancy between wage and employment adjustments can be a consequence of firms' passing-through adverse effects of competition to their employees by lowering wages and/or of firms' reorganizing their workforce (i.e. churning).

Remarkably, firms have a completely different long-term strategy in response to the distinct types of competition: We find that surviving firms faced with competition from low-income countries increase their R&D spending, presumably in an attempt to upscale their products or to discover a different market. Although we do not find any direct positive effects of low-income import competition on firm productivity, this increase in R&D activities suggests a potential for future productivity gains that are not yet realized one year after an

[25] Given that P_{it} is already reported in percentage changes relative to the base year, we did not take the log of it. We deflated w_{it} and $r\&d_{it}$ with the CPI.
[26] Otherwise we would need to define a more complex count data model.

import competition shock (see also Bloom, Draca, & Van Reenen (2016) in that respect). In contrast, R&D spending in firms facing competition from high-income countries seems to be victimized by the same cost saving impulses as other expenditures.

An important implication of this latter finding is, that R&D investments cannot explain the increase in productivity from high-income import competition. Instead, high-income import competition increases firm productivity by forcing a more efficient use of production inputs that translates into a reduction in total input expenditures while keeping output quantities constant. This is likely associated with a reduction in so-called X-inefficiencies within firms (e.g. Leibenstein (1966); Stigler (1976)).

Such X-inefficiencies are often seen as a form of rent consumption by non-shareholders (Biggerstaff et al. (2016)). If this is true, then fiercer competition increases the price of this consumption. Theoretically, as demand curves become flatter, minor differences in productivity can lead to hugely different profit outcomes. Consequently, tighter competition will force firms to monitor their production processes (and employees) more strictly. As high-income competition erodes the firms' (monopoly) rents, we interpret our findings as cross-industry causal evidence for this behavior. Something the literature is yet lacking, although a number of specialized studies exist (e.g. Borenstein & Farrell (2000); Bloom et al. (2015)).[27]

[27] A related strand of the literature interprets X-inefficiencies as information frictions: In a large survey of manufacturing firms, Bloom & Van Reenen (2010) and Bloom, Genakos, Sadun, & Van Reenen (2012) showed that managers systematically overestimate the performance of their own management practices. Loosing market shares to competitors from countries similar to Germany might disabuse managers of that notion leading them to reorganize their production processes.

TABLE 2.5

FIRM ADJUSTMENTS AND IMPORT COMPETITION

	$\tilde{r}_{it}$ (1)	q_{it} (2)	P_{it} (3)	l_{it} (4)	w_{it} (5)	$\tilde{k}_{it}$ (6)	$\tilde{m}_{it}$ (7)	$r\&d_{it}$ (8)
IMP_{it-1}^{High}	-0.0129*	0.0010	-0.00646*	-0.0052	-0.0097**	-0.0099*	-0.0131*	-0.0870***
	(0.0068)	(0.0067)	(0.0036)	(0.0041)	(0.0047)	(0.0060)	(0.0073)	(0.0317)
IMP_{it-1}^{Low}	-0.0060***	-0.0059***	0.00079	-0.0031**	-0.0035**	-0.0029**	-0.0062***	0.0314**
	(0.0021)	(0.0023)	(0.0011)	(0.0014)	(0.0014)	(0.0015)	(0.0022)	(0.0154)
Firm $*$ Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	78,414	78,414	78,414	78,414	78,414	78,414	78,414	26,544
R-squared	0.987	0.985	0.836	0.985	0.989	0.992	0.986	0.909
First-stage F-test	36.89	36.89	36.89	36.89	36.89	36.89	36.89	17.55
Number of firms	16,925	16,925	16,925	16,925	16,925	16,925	16,925	5,305

Notes: Table 2.5 reports results from estimating equation (2.10) by IV. The dependent variable in columns (1)-(8) respectively is a firm's logged revenue, logged produced quasi-quantity, output price index, logged full time equivalents, logged average wage, logged capital stock, logged intermediate input expenditures, and logged R&D expenditures. All regressions are weighted using inverse probability weights and include controls for firms' export intensity and number of products. Standard errors are clustered at the firm level. Significance: *10 percent, **5 percent, ***1 percent.

2.7 Conclusion

This study analyzes how import competition affects firm productivity. To address our research questions, we rely on a comprehensive administrative dataset on German manufacturing sector firms containing price and quantity information on firms' final products. Based on that data, we derive a quantity-based productivity measure that isolates changes in firms' technical efficiency from changes in firms' output prices.

We document a positive effect of import competition on firm productivity, which is driven by import competition from high-income countries. In contrast, competition from low-income countries has no direct effect on firm productivity but causes firms to invest in R&D. This increase in R&D expenditures might translate into long-run productivity improvements that we do not capture in our empirical specification.

Our findings show that the productivity enhancing effect of high-income countries' import competition is not a consequence of German firms investing in R&D. Instead, it results from firms using less inputs to produce the same amount of output. Consumers benefit from the induced cost savings by paying lower output prices.

We argue that the documented productivity gains can only be explained if firms are not operating at their maximum efficiency level. There is compelling evidence that firms indeed exhibit sizeable slack which explains a large part of the observed productivity dispersion between firms (Bloom, et al. (2012)). For instance, firms' managers might consume a part of their firm's profits as leisure (Biggerstaff, et al. (2016). Theoretically, competition should exert pressure towards efficiency. Empirically, this has so far only been shown in highly specific cases (e.g. Borenstein & Farrell (2000); Bloom, et al. (2015)). Our study provides first empirical cross-industry evidence that competition activates *already existing but unexploited* productivity reserves.

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Appendix A

A.1 Sample summary statistics

Table A.1 displays summary statistics for our sample of firm entering our final estimation of the effect of import competition on within-firm productivity.

TABLE A.1

SUMMARY STATISTICS FOR SAMPLE FIRMS

Variable	Mean (1)	SD (2)	P25 (3)	Median (4)	P75 (5)	Observations (6)
Firm productivity	2.82	0.85	2.26	2.72	3.21	78,414
Deflated revenue in thousands (industry price index)	97,600	1,21,000	5,443	14,200	44,200	78,414
Full-time equivalents	351.10	2773.90	47	98	244	78,414
Deflated capital stock in thousands	61,000	613,000	2,662	8,220	28,200	78,414
Deflated intermediate input expenditures in thousands	70,700	973,000	3,088	8,734	28,800	78,414
Deflated capital per full-time equivalent in thousands	118.25	130.15	43.57	81.28	145.77	78,414
Export intensity (share of export revenue in total sales)	23.86	25.16	0.54	16.46	40.31	78,414
Export status dummy	0.78	0.42	1	1	1	78,414
R&D status dummy	0.35	0.48	0	0	1	78,414
Average deviation of firms' product prices from industry-wide product prices	3.19	11.40	0.90	1.26	2.23	78,414
Number of products	4.04	8.53	1	2	4	78,414
Total import competition	5.45	10.53	0.04	0.97	5.74	78,117
High-income import competition	1.70	4.20	0	0.15	1.42	78,117
Low-income import competition	3.75	9.02	0.02	0.40	2.97	78,117

Notes: Table A.1 reports summary statistics for sample firms. 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. As the statistics are based on the sample of firms entering the estimation described by equation (2.10) of the main text, the observation count on the contemporaneous import competition measures is lower compared to other variables.

A.2 Deriving a firm-specific price deflator

We construct a firm-specific price index to purge firm revenues from price variation. The calculation of this price index closely follows Eslava, Haltiwanger, Kugler, & Kugler (2004). In particular, we construct a firm-specific Törnqvist index for each firm's composite revenue from its various products:

$$P_{it} = \prod_{g=1}^{n} \left(\frac{p_{igt}}{p_{igt-1}}\right)^{\frac{1}{2}(s_{igt}+s_{igt-1})} P_{it-1}, \tag{A.1}$$

where p_{igt} is the price of good g and s_{igt} is the corresponding share of this good in the output of firm i in period t. Thus, the growth of the index value is the product of the individual products' price growths, each weighted with the average revenue share of that product over the current and the last year. We use the first year available in the data as our base year, i.e. we set $P_{t=2000} = 100$. For firms entering after 2000, we use 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 (for some products, firms do not have to report quantities because they would not be meaningful).

A.3 Construction of capital stock series

We construct capital stocks at the firm level using a perpetual inventory method. To estimate the first capital stock of every series, we combine information on the value of yearly depreciations of firms, denoted by τ_{it} and which is included in the AFiD-data, with information on the average lifetime of capital goods, $D_t(\Theta)$, where $\Theta = (equipment, buildings)$ highlights that this information exists separately for building and equipment capital (this information is provided by the Federal Statistical Office of Germany). For now, let us abstract from the different capital good types. Note that the lifetime of capital goods contains information about their real depreciation rate.[28] As standard in the literature, we assume that capital depreciates at a constant rate and that it is fully destroyed (depreciated) at the end of its lifetime. Let us define the amount of capital which depreciated during the production process in industry j and period t as:

$$\varphi_{jt} = \delta_{j0} K_{jt}, \tag{A.2}$$

where δ_{j0} is the depreciation rate of capital purchased at time $t = 0$. The average lifetime of a capital stock purchased in year $t = 0$ then equals:

$$D_{j0} = \frac{1}{K_{j0}} \sum_0^\infty \varphi_{jt} t = \frac{1}{K_{j0}} \sum_0^\infty \left(\delta_{j0} K_{jt}\right) t, \tag{A.3}$$

With a little algebra, one can show that assuming a linear capital depreciation, $K_{jt} = K_{j0}\left(1 - \delta_{j0}\right)^t$, and substituting it into (A.3) gives:

$$D_{j0} = \frac{\delta_{j0}}{\ln(1-\delta_{j0}) * \ln(1-\delta_{j0})}\,.\text{[29]} \tag{A.4}$$

[28] Ultimately, we augment an approach from Müller (2008) by backing out the implied depreciation rate in a way that is consistent with a constant depreciation rate, the prevailing assumption in the literature.
[29] The prove is available on request.

As $D_{jt}(\Theta)$ is known, we can recover δ_{jt} by solving this expression numerically for each year and each capital type, $\Theta = (equipment, buildings)$. This generates two depreciation rates for each point in time. We then define a single industry-specific depreciation rate by using the shares of the industry-wide stocks of equipment and building capital at time t as weights. Finally, we simplify by assuming that the depreciation rate for the entire capital stock in each period equals the depreciation rate of newly purchased capital, i.e. $\delta_{j0} = \delta_{jt}$.

Having calculated δ_{jt}, we can recover a starting capital stock for every firm by using information on the value of yearly depreciations, $DEPR_{it}$, from the AFiD-database:

(A.5) $$K_{it} = DEPR_{it}/\delta_{jt}.$$

Now we can compute our capital series by:

(A.6) $$K_{it} = K_{it-1}(1 - \delta_{jt-1}) + I_{it-1}.$$

where, I_{it} denotes firm-specific investment.[30]

As our capital stocks are based on information on the lifetime of capital goods, they are closer approximations of the capital actually used in firms' production activities than capital stocks based on book values. This is because firms might buy and sell their capital goods not to market prices and have incentives to depreciate their accounting capital excessively (House & Shapiro (2008)).

[30] We deflated $DEPR_{it}$ and I_{it} respectively by an industry-specific capital depreciation and investment deflator. Both deflators are supplied by the Federal Statistical Office of Germany.

A.4 First stage regressions

In the following we present the first stage regressions belonging to our results presented in the main text. As we always use the same instruments to instrument the same endogenous variables, our first stage regressions are identical for all regressions using the same set of firms. Hence, we only show two sets of first stage regressions. One for the full sample firms and one for the sample of firms engaging in R&D activities. Those first stage regressions are respectively reported in Table A.2 and Table A.3.

Table A.2

FIRST STAGE REGRESSION RESULTS, FULL SAMPLE

	$IMP_{it-1}^{High+Low}$ (1)	IMP_{it-1}^{High} (2)	IMP_{it-1}^{Low} (3)
$IS_{it-1}^{High+Low \rightarrow third}$	0.235*** (0.0197)	-	-
$IS_{it-1}^{High \rightarrow third}$	-	0.0995*** (0.0117)	0.0314*** (0.0111)
$IS_{it-1}^{Low \rightarrow third}$	-	0.0156*** (0.0051)	0.279*** (0.0224)
Firm x Industry FE	YES	YES	YES
Time FE	YES	YES	YES
Firm-level controls	YES	YES	YES
Observations	78,414	78,414	78,414
R-squared	0.950	0.927	0.946
Number of firms	16,925	16,925	16,925

Notes: Table A.2 reports results from the first stage regressions when estimating equation (2.10) by IV using the full sample of firms. The dependent variable in columns 1,2, and 3 respectively is the lagged total import competition measure, the lagged high-income import competition measure, and the lagged low-income import competition measure. All regressions include time and industry times firm fixed effects and controls for firms' number of products and export intensity. Standard errors are clustered at the firm level. Significance: *10 percent, **5 percent, ***1 percent.

TABLE A.3

FIRST STAGE REGRESSION RESULTS,
R&D-FIRM SAMPLE

	IMP_{it-1}^{High} (1)	IMP_{it-1}^{Low} (2)
$IS_{it-1}^{High\rightarrow third}$	0.118***	0.0210
	(0.0205)	(0.0176)
$IS_{it-1}^{Low\rightarrow third}$	0.0308***	0.228***
	(0.0109)	(0.0299)
Firm x Industry FE	YES	YES
Time FE	YES	YES
Firm-level controls	YES	YES
Observations	26,544	26,544
R-squared	0.928	0.952
Number of firms	5305	5305

Notes: Table A.3 reports results from the first stage regressions when estimating equation (2.10) by IV using firms that engage in R&D-activities. The dependent variable in columns 1 and 2 respectively is the lagged high-income import competition measure and the lagged low-income import competition measure. All regressions include time and industry times firm fixed effects and controls for firms' number of products and export intensity. Standard errors are clustered at the firm level. Significance: *10 percent, **5 percent, ***1 percent.

References (Appendix A)

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Chapter 3

Labor Market Power and the Distorting Effects of International Trade

3.1 Introduction

WELFARE GAINS FROM GLOBAL INTEGRATION ARE NOT INCLUSIVE. Instead, trade creates winners and losers. While international trade benefits some agents of an economy, we know that trade causes certain worker groups to suffer from tremendous welfare losses, increases wage inequality, and, thereby, even magnifies political polarization.[31]

In principle, all those distributional effects can be rationalized within a simple Heckscher-Ohlin framework. Lately, however, economists have raised awareness to the role of imperfect functioning labor markets in distributing and realizing gains from trade (e.g. Egger & Kreickemeier (2009); Kambourov (2009); Dix-Carneiro (2014)). Imperfect labor markets not only imply distributional effects from trade, but they also affect aggregate trade gains compared to a standard model with competitive labor markets. Therefore, understanding how international trade interacts with labor market imperfections has a first order priority in evaluating welfare effects and distributional impacts from trade liberalization.

This article contributes to this understanding by developing a simple micro-econometric partial equilibrium framework to investigate how international trade causally affects and interacts with labor market distortions in the German manufacturing sector. The framework in this article does not depend on specific demand side characteristics as it only relies on

[31] E.g. Verhoogen (2008); Egger and Kreickemeier (2009); Autor, Dorn, & Hanson (2013); Dix-Carneiro (2014); Autor, Dorn, & Hanson (2014); Autor, Dorn, Hanson, & Majlesi (2016); Dippel, Gold, Heblich, & Pinto (2017); Helpman, Itskhoki, Muendler, & Redding (2017); Yi, Müller, & Stegmaier (2017).

production side information. It identifies distortions in labor markets by firm-level wedges between workers' output contributions and wages. The existence of such wedges reflects market power in labor markets that affects distributional outcomes and signals market inefficiencies that decrease aggregate output (Petrin & Sivadasan (2013)).

Intuitively, international trade has the potential to affect and interact with labor market distortions through different channels: On the one hand, trade influences firms' labor demand and gives an impetus for reorganizing existing structures within firms as well as for reallocating labor between firms.[32] On the other hand, international trade sets political incentives for improving the efficiency of domestic labor markets by exerting competitive pressure on existing labor market institutions (Boulhol (2009)). Moreover, as labor market distortions create reallocation barriers and influence the rent sharing between firms and employees, existing distortions might determine how firms adjust their labor expenses in response to trade exposure. However, how international trade influences labor market imperfections, to what extent prevalent labor market distortions determine distributional outcomes from trade, and whether trade can function as a disciplining tool for distorted labor markets remain open empirical questions that this study aims to answer.

While doing so, this article adds two new insights to the literature. First, it presents new evidence on the causal effect of trade on firms' labor market power. This contributes to our understanding on how exactly international trade influences rent sharing processes between employees and their firms. Second, this study presents first empirical results on the causal effect of international trade on market inefficiencies emerging from imperfect labor markets. This offers insights on potential gains (losses) from trade in terms of labor market efficiency, a topic on which our knowledge is rather limited, so far.

[32] E.g. Bernard, Redding, & Schott (2011); Caliendo & Rossi-Hansberg (2012); Mayer, Melitz, & Ottaviano (2014); Caliendo, Monte, & Rossi-Hansberg (2017).

My main results document that an increase in export demand strengthens the labor market power of firms, whereas, oppositely, import competition increases employees' labor market power. When uncovering the mechanisms behind those effects, I find that existing structures of labor market power prevent a complete adjustment of firms' labor expenses. Firms with labor market power do not fully pass-through export profit gains to workers, whereas firms with a workforce that possesses labor market power increase wages and employment in response to increasing foreign demand. Complementarily, I find that firms facing a workforce with positive labor market power cannot fully adjust to import competition by shrinking or lowering wages. Those incomplete pass-through processes increase existing labor market distortions and, therefore, decrease the efficiency of labor markets. Hence, due to imperfect labor market adjustments, international trade can increase gaps between realized and potential output, which prevents a full realization of classical gains from trade. In addition, I find some evidence for labor market disciplining effects from import competition. However, those disciplining effects are extremely sensitive to the empirical specification and only occur when firms rather than employees possess labor market power.

To conduct my analysis, I use administrative firm-product-level data for the German manufacturing sector. I can exploit the eight-digit product-level information in this data to calculate exceptionally fine measures of final product import competition and export opportunities for every individual firm. Measuring trade flows at the firm rather than the industry level reduces mismeasurement in the explanatory variables, creates additional identifying variation, and accounts for the presence of multi-product firms that are active in multiple industries. In line with most of the trade literature, the analysis of this article focuses on trade with China, whose unexpected and rapid rise to dominance in the global market offers an excellent playing field to study the effects of international trade on labor market outcomes (Autor, Dorn, & Hanson (2016)). To draw causal inferences, I instrument my trade measures in the spirit of Autor et al. (2013) and Dauth, Findeisen, & Südekum (2014, 2018) by using trade flows between China and countries similar to Germany.

This study ties into a long run strand of the literature investigating how international trade affects wage bargaining processes. Rodrik (1997) already noted that imported products substitute domestic with foreign workers, weakening the position of the former within the firm. Carluccio, Fougère, & Gautier (2016) find that an increase in foreign demand raises the probability of signing firm-level collective wage agreements. Moreover, for the UK, Hornstein, Krusell, & Violante (2005) provide evidence that competitive pressure may lead to deunionisation. Most closely related to this paper, Boulhol, Dobbelaere, & Maioli (2011) find a negative impact of imports from developed countries on workers' bargaining power for the UK, while Nesta & Schiavo (2018), by focusing on the subset of firms within an efficient bargaining regime, find the same for imports from China and OECD countries in the case of France. Similarly, Ahsan & Mitra (2014) document that a reduction in output tariffs is associated with a decrease in workers' bargaining power for India. However, my study complements all mentioned contributions in several aspects. First, in contrast to this study, existing work does not investigate the causal link between labor market efficiency and international trade. Instead, it focuses on the distributional aspects. Second, I do not restrict the causal analysis to import competition. In fact, I find that labor market distortions react three to four times stronger to an increase in foreign demand than to an increase in import competition. Third, my results show that international trade interacts with existing structures of labor market distortions and tends to fortify prevalent labor market imperfections. In particular, firms with and without labor market power do not react uniformly to trade exposure. Instead, international trade tends to increase absolute labor market power levels, which is reflected in a widening of existing positive and negative firm-level gaps between marginal products and wages. This is exactly the source of losses in terms of labor market efficiency from trade.

My study is also closely related to recent work that investigates how labor market frictions interact with trade by estimating dynamic general equilibrium models (e.g. Artuç, Chaudhuri, & McLaren (2010); Dix-Carneiro (2014); Coşar, Guner, & Tybout (2016)). Traditionally, those models define specific labor market frictions that are exogenous with respect to trade and explicitly describe how those frictions relate to worker reallocation, wages, and welfare. Although similar in spirit to this literature, my study does not focus on the general equilibrium and, therefore, imposes less structure to the data. This allows me to be agnostic about the underlying preference structures and sources of labor market distortion. Moreover, my framework does not invoke any a priori assumptions on the relation between trade and labor market imperfections and considers that trade might itself affect specific frictions.

Finally, this article complements recent work discussing how incomplete pass-through processes of trade related productivity gains to consumer prices give rise to output market distortions. De Loecker, Goldberg, Khandewal, & Pavcnik (2016) find that Indian firms do not fully pass-through productivity gains from cheaper imported intermediate products to consumer prices, increasing firm-markups. Arkolakis, Costinot, Donaldson, & Rodríguez-Clare (2018) show that under non-homotheticity in preferences it is unclear whether trade integration increases or decreases output market distortions. Weinberger (2017) illustrates this by incorporating a possible non-optimal market share reallocation into the Melitz (2003) model. In his model, heterogeneous output market power allows firms to heterogeneously pass-through productivity gains from cheaper imported inputs to consumer prices. Through this mechanism, more productive firms increase their markups relatively more, which reallocates production to the less efficient firms, giving rise to misallocation.

In a sense, my study transfers these findings for output market distortions to labor markets. Closely related to this literature, I find that the underlying mechanism giving rise to labor market distorting effects from trade is based on an incomplete pass-through from trade related firm profit changes to workforce adjustments. That international trade has the potential to worsen the efficiency of labor markets is an alarming finding, as it implies that models assuming competitive labor markets might overestimate the gains from trade.

The remainder proceeds as follows. Chapter 3.2 describes the data and explains the construction of trade measures. In chapter 3.3 I derive the framework for measuring labor market distortions in monetary terms. Chapter 3.4 presents the empirical results and chapter 3.5 tests for their robustness. Chapter 3.6 concludes.

3.2 Data description and calculating trade measures

I use yearly data on German manufacturing sector firms over the period 2000-2014 from the AFiD-database. The data is supplied by the statistical offices of Germany and consists of two complementary parts.[33] The first is a firm-level panel for the years 2000-2014, containing, among others, data on expenditures, output, employment, and investment. The second part is a firm-product-level panel for the period 1995-2014, supplying information on

[33] Data source: Research Data Centre of the Federal Statistical Office of Germany and the Statistical Offices of the German Länder. Names of statistics used: *"AFiD-Modul Produkte"*, *"AFiD-Panel Industriebetriebe", "AFiD-Panel Industrieunternehmen", "Investitionserhebung im Bereich Verarbeitendes Gewerbe, Bergbau und Gewinnung von Steinen und Erden", "Panel der Kostenstrukturerhebung im Bereich Verarbeitendes Gewerbe, Bergbau und Gewinnung von Steinen und Erden"*.

quantity and prices for each firms' products. As firms are obliged to answer, this data is of comparably high quality and contains only a negligible amount of missing values.[34]

AFiD is limited to firms with at least 20 employees. To reduce administrative burden, some variables in the firm-level panel are only available for a representative and periodically rotating subsample encompassing roughly 40% of firms with at least 20 employees. Among others, this contains expenditures on intermediate inputs or employment in full time equivalents (FTE). As this subsample is stratified according to size class and industry, which are variables that I observe for all firms, I can use inverse probability weights to translate all of my regression results to the underlying population of German manufacturing firms (with at least 20 employees).

Bilateral trade flow data comes from the United Nations Comtrade Database (comtrade). The product dimension of AFiD allows me to calculate trade measures at the disaggregated firm-product level by using information on firms' product mix. Relying on firm-product- rather than on industry-level trade flows ensures that I do not mix up final product with intermediate input trade and that I account for multi-product firms being simultaneously active in multiple industries.[35]

In some cases, export values reported in comtrade exceed domestic production reported in AFiD, which could be a result of the reporting threshold of the AFiD data. Therefore, I follow Mion & Zhu (2013) and define Chinese product-level import competition, $IM_{gt}^{CHN\rightarrow GER}$, as the period t share of product g imports from China to Germany, $M_{gt}^{CHN\rightarrow GER}$, in the sum of

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[34] I eliminate observations with negative value-added and outliers with respect to deflated sales over production inputs. I also purge the product data from outliers in terms of price growth and price deviations from the average product price.

[35] I focus on final product trade as I do not have information on firms' intermediate input imports. Intermediate input trade may exert different effects on my variables of interest (e.g. De Loecker & Goldberg (2014).

Germany's total imports and total domestic production of product g (from plants with at least 20 employees), respectively denoted by M_{gt} and Y_{gt}:

(3.1)
$$IM_{gt}^{CHN\rightarrow GER} = \frac{M_{gt}^{CHN\rightarrow GER}}{M_{gt} + Y_{gt}} * 100.$$

Complementarily, I define export opportunities for German products as:

(3.2)
$$EX_{gt}^{GER\rightarrow CHN} = \frac{E_{gt}^{GER\rightarrow CHN}}{M_{gt} + Y_{gt}} * 100.$$

where $E_{gt}^{GER\rightarrow CHN}$ denotes product g exports from Germany to China. As I discuss in my empirical section, I instrument those two measures with trade flows between China and countries similar to Germany. I aggregate all product-level trade flow measures to the firm level by using firm-specific product revenue shares in firms' total product market revenue as weights. I denote the resulting firm-level measures by IMP_{it}^{CHN} and EXP_{it}^{CHN} and plot their evolution in Appendix B.1.

3.3 A framework to estimate labor market distortions

This section describes the framework to estimate labor market distortions. Section 3.3.1 starts by deriving a monetary quantifiable expression for labor market distortions. I discuss the interpretation of this parameter in section 3.3.2. Section 3.3.3 continues with a detailed treatment of the production function estimation needed to calculate firm-specific labor market distortion parameters.

3.3.1 Deriving an expression for labor market distortions

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

(3.3) $$Q_{it} = Q_{it}(.) = Q_{it}(L_{it}, M_{it}, K_{it}, \omega_{it}),$$

where Q_{it} denotes total physical output and L_{it}, M_{it}, and K_{it} respectively are labor, intermediate, and capital inputs used in the production of Q_{it}. ω_{it} denotes total factor productivity. The only restriction on the functional form of $Q_{it}(.)$ that I impose is that it is continuous and twice differentiable with respect to its arguments. Active firms maximize short run profits and face time and firm specific unit input cost for any input $X = \{L, K, M\}$, denoted by V_{it}^{X}. Intermediate inputs are flexible and firms take intermediate input prices as given. Contrary, labor and capital markets are imperfect. Hence, those inputs markets are subject to distortions that create wedges between firms' marginal costs and marginal products. Importantly, as shown in Petrin & Sivadasan (2013), such micro-level wedges signal market inefficiencies that reduce total output at the macro-level (see the discussion below).

As I am interested in labor market imperfections, I will now focus on labor markets. I introduce labor market distortions as monetary wedges, $\delta_{it}^{L} \equiv f_{it}(\boldsymbol{S}_{it})$, between observed wages and marginal revenue products of labor (MRPL):

(3.4) $$f_{it}(\boldsymbol{S}_{it}) = \delta_{it}^{L} = V_{it}^{L} - MRPL_{it}.$$

The vector $\boldsymbol{S}_{it}$ captures the sources of labor market distortions and describes their mapping into deviations from the competitive labor market scenario ($V_{it}^{L} = MRPL_{it}$). If labor market distortions were solely resulting from firms' wage setting power (i.e. a monopsonistic labor market model), observed wages would be given by $V_{it}^{L} = MRPL_{it} + f_{it}(\varepsilon_{it}^{L})$, with $f_{it}(\boldsymbol{S}_{it}) = f_{it}(\varepsilon_{it}^{L}) < 0$ and ε_{it}^{L} denoting the supply elasticity of labor. Such a model has been recently discussed in Tortarolo & Zárate (2018) to which I refer for more details. However, as labor market distortions are an outcome of a variety of frictions, limiting the analyses to the monopsonistic labor market model as above is restrictive. For instance, $f_{it}(\boldsymbol{S}_{it})$ may also depend on the presence of hiring and firing costs, search frictions, inflexible contracts, imperfect information, trade unions, or workers' bargaining power. In fact, many studies invoke extreme assumptions on the exogeneity of wages or the flexibility of labor to identify a specific kind of friction from observed wedges between wages and marginal products of labor (e.g. Hsieh & Klenow (2009); Petrin & Sivadasan (2013)). Yet, such extreme assumptions do not change the nature of what we measure in the data. Therefore, I stay agnostic about the underlying frictions included in $\boldsymbol{S}_{it}$ and abstain from restricting $f_{it}(\boldsymbol{S}_{it})$ to a specific price or quantity distortion.

Consequently, my approach nests a variety of labor market models, including models that generate an outcome where $V_{it}^{L} > MRPL_{it}$. The latter can, for instance, result from an efficient bargaining regime as discussed in Dobbelaere & Mairesse (2013), where unions have some degree of bargaining power, ϕ_{it}, and wages are a result of a Nash-bargaining between firms and unions: $V_{it}^{L} = MRPL_{it} + f_{it}(\phi_{it}, \Pi_{it})$, with Π_{it} denoting profits and $f_{it}(\phi_{it}, \Pi_{it}) > 0$. Similarly, I allow for $V_{it}^{L} \neq MRPL_{it}$ as a consequence of labor hoarding, as in Rebitzer & Taylor (1991), or as a result of hiring and firing costs, as in Petrin & Sivadasan (2013).

The problem in using equation (3.4) is to recover a consistent measure of $MRPL_{it}$. To circumvent this problem, I follow Dobbelaere & Mairesse (2013) in using the intermediate input market as a competitive benchmark to express δ_{it}^{L} as a function of measurable variables. In Appendix B.2, I show that this translates into:

$$\delta_{it}^{L} = V_{it}^{L} - \frac{\theta_{it}^{L}}{\theta_{it}^{M}} * \frac{V_{it}^{M} M_{it}}{L_{it}}, \tag{3.5}$$

where θ_{it}^{X} denotes the output elasticity with respect to input X.

Assuming competitive intermediate input markets to identify labor market distortions builds upon a large literature on estimating markups and firm productivity by control function approaches in which exactly this assumption is key in ensuring identification. Yet, in my results section, I address potential concerns about biases introduced by non-competitive intermediate input markets when estimating the impact of international trade on δ_{it}^{L}.

Equation (3.5) can be linked to the current workhorse framework of Dobbelaere & Mairesse (2013), in which labor market distortions are given by the difference between $\mu_{it}^{M} = \theta_{it}^{M} * \frac{P_{it}Q_{it}}{V_{it}^{M}M_{it}}$ and $\mu_{it}^{L} = \theta_{it}^{L} * \frac{P_{it}Q_{it}}{V_{it}^{L}L_{it}}$. Here, μ_{it}^{M} and μ_{it}^{L} respectively denote the firm's markup derived from the firm's input decision for intermediates and labor using the framework of De Loecker & Warzynski (2012). To see the similarity between the approach in this article and the framework of Dobbelaere & Mairesse (2013), note that equation (3.5) can be rewritten as $\delta_{it}^{L} = V_{it}^{L} - \frac{\mu_{it}^{L}}{\mu_{it}^{M}} V_{it}^{L}$. Consequently, the measure of Dobbelaere & Mairesse (2013) implies the value of δ_{it}^{L}.[36] The advantage of the approach in this study is that I express labor market distortions in monetary terms, which enables intuitive interpretations of labor markets imperfections.

3.3.2 Labor market power, adjustment frictions, and market inefficiencies

δ_{it}^{L} captures the extent to which labor market imperfections, separately from product market imperfections, drive a wedge between marginal products of labor and wages. When $\delta_{it}^{L} > 0$, wages are higher than workers' output contribution. This creates an outcome in which rents are inefficiently distorted towards employees (vice versa for $\delta_{it}^{L} < 0$). Similar to

[36] See Appendix B.2 for a discussion. I also show in Appendix B.3 that μ_{it}^{M} displays a clearly larger dispersion than μ_{it}^{L} across firms. This is consistent with intermediate input markets being more competitive than labor markets.

Dobbelaere & Mairesse (2013), I interpret δ_{it}^{L} as an inverse measure of firms' labor market power, i.e. negative (positive) values of δ_{it}^{L} signal labor market power of the firm (firm's workforce).

An important precondition for the existence of market power in labor markets is the presence of adjustment frictions that firms and employees utilize to their advantage (e.g. Manning (2003); Naidu, et al. (2018)). For instance, moving costs of employees that can be exploited by firms are a typical argument for the existence of monopsonistic labor markets on which firms pay below competitive wages (Manning (2003)). On the other hand, workers might exploit inflexible contracts to spend only low effort levels, such that their compensation is above their output contribution (this is similar to a labor hoarding model). Note that in this case, the market power of employees is not a result of wage bargaining power in the classical sense. It is instead a result of firms' being institutionally restricted in their labor quantity and wage adjustments. Strictly speaking, also efficient bargaining models, where firms and unions bargain with each other, model a hiring friction to generate an outcome where $V_{it}^{L} > MRPL_{it}$. Here, union members coordinate their supply of labor and firms are *restricted* to only hire workers from the union (McDonald & Solow (1981)).

Whereas δ_{it}^{L}, reflects the distribution of (market power) rents between firms and employees, absolute values of δ_{it}^{L} measure firms' contribution to the total extent of labor market inefficiencies (compared to a socially optimal neo-classical benchmark scenario). This is because perfect labor markets would eliminate every positive and negative gap between wages and MRPL. Petrin & Sivadasan (2013) illustrate this within a simple accounting framework and show that larger *levels* of absolute gaps between wages and MRPL signal a larger potential for output increasing reallocation and therefore imply a larger gap between realized and potential output. Hence, defining *levels* of $\left|\delta_{it}^{L}\right|$ as a measure of firms' contribution to total labor market inefficiencies follows the work of Petrin & Sivadasan (2013).[37] Note, however, that this also nicely links into the above definition of labor market power, as, intuitively, firms with labor market power demand too few workers, whereas workers with labor market power prevent firms from shrinking. From an efficiency perspective, labor market power creates distortions where too *much* labor is allocated to firms with $\delta_{it}^{L} > 0$ and too *little* labor is allocated to firms with $\delta_{it}^{L} < 0$.

Before using equation (3.5), I first need to recover θ_{it}^{L} and θ_{it}^{M} by estimating a production function. As firm-level prices are regularly unobserved, researchers are often forced to assume that input and output prices equalize between firms within industries when estimating the production function. This is hardly compatible with allowing for firm-specific labor market power. As I observe firm-product-level prices, I can account for firm-specific price variation. Yet, although theoretically important, correcting for firm-level price variation only marginally affects responses of labor market distortions to final product trade in my case. Still, as shown in Appendix B.4, ignoring firm price variation *increases* levels of δ_{it}^{L} in my case, leading to a higher share of firms and industries in which employees possess labor market power.

3.3.3 Production function estimation

I use a translog specification to define firms' production function because it allows for *time varying and firm specific* output elasticities. For estimation, I define M_{it}, K_{it}, L_{it}, and Q_{it} as a

[37] Note that this concept is different from the Hsieh & Klenow (2009) framework, where between-firm dispersion in such wedges is interpreted as a misallocation measure. Similar to Petrin & Sivadasan (2013), recent work by Morlacco (2018) provides a theoretical framework showing that *levels* of wedges between input costs and marginal products of input indicate market inefficiencies that reduce aggregate output compared to a counterfactual scenario with competitive input markets.

firm's intermediate inputs, capital stock, FTE, and total output, respectively.[38] The production function is given by:

$$q_{it} = \boldsymbol{\phi}'_{it}\boldsymbol{\beta} + \omega_{it} + \varepsilon_{it}. \tag{3.6}$$

Lower-case letters indicate logs. $\boldsymbol{\phi}_{it}$ is a vector capturing production inputs and their interactions, $\boldsymbol{\beta}$ is the associated vector of coefficients and ε_{it} is an i.i.d. error term.[39] Hicks-neutral productivity, ω_{it}, follows a Markov process that can be influenced by firm actions and is unobserved to the econometrician. The firm knows ω_{it} before choosing its consumption of intermediate inputs. The innovation in productivity is, however, uncorrelated with the input decision for capital and labor. This is consistent with labor and capital both facing adjustment costs but labor being more flexible than capital.[40] Due to the dependence of firms' intermediate inputs on ω_{it}, estimation of equation (3.6) by OLS is inconsistent. Besides this simultaneity problem, firm-specific prices are usually unobserved. Hence, if input prices are correlated with input choices, estimating (3.6) without controlling for firm price variation produces biased input coefficients.

3.3.3.1 Unobserved output and input prices

Due to differences in measurement units, I cannot aggregate output quantities for multi-product firms. Therefore, I construct firm-specific output price indices following the procedure of Eslava, Haltiwanger, Kugler, & Kugler (2004). I purge observed firm revenue

[38] The calculation of capital stocks follows Bräuer, Mertens, & Slavtchev (2019) and is based on Müller (2008). The law of motion for capital is: $K_{it} = (1 - \alpha_{jt})K_{it-1} + I_{it-1}$. I_{it} and α_{jt} respectively denote investment and the industry j and time specific depreciation rate. Long-term rentals are part of the capital stock.

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

[40] Those timing assumptions are consistent with several other studies (e.g. in De Loecker et al. (2016) for India, Valmari (2016) for Finland, and Ackerberg & Hahn (2015) for Chile). Due to the Germany's high degree of employment protection (OECD 2018), it seems justified to treat labor as a quasi-fixed input in my case.

(for all firms) from output price variation by deflating it with this price index. With slightly abusing notation I keep using q_{it} for the resulting quasi-quantities. To control for unobserved input price variation, I follow De Loecker et al. (2016) who have shown that for general models of demand, market shares and product dummies approximate product quality. Consequently, by assuming that producing high quality goods requires high quality inputs, one can use a single quality control function to absorb input price variation:

$$B_{it}(.) \equiv B_{it}\big((\pi_{it}, \boldsymbol{ms}_{it}, G_{it}, D_{it}) \times \boldsymbol{\phi}_{it}^{c}; \boldsymbol{\beta}\big). \tag{3.7}$$

Here, $\boldsymbol{ms}_{it}$ captures domestic quantity and revenue market shares, π_{it} is a firm-level price index and G_{it} and D_{it} contain dummies for headquarter location and four-digit industry affiliation. $\boldsymbol{\phi}_{it}^{c} = \{1; \widetilde{\boldsymbol{\phi}}_{it}\}$ contains two vectors. $\widetilde{\boldsymbol{\phi}}_{it}$ includes the same production input terms as $\boldsymbol{\phi}_{it}$, either given in expenditures and deflated by an industry-level deflator or already reported in quantity terms. The tilde emphasizes that some variables in $\widetilde{\boldsymbol{\phi}}_{it}$ are not expressed in true quantities. The constant highlights that other elements of $B(.)$ enter the price control function linearly and interacted with $\widetilde{\boldsymbol{\phi}}_{it}$ (which follows from using a translog production function).

This specification captures unobserved input price variation that arises from variation in firms' input quality, location, and industry affiliation. Note that the inclusion of a price control function does not demand that prices between firms vary 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. Finally, using output prices to control for input price quality does not imply a complete pass-through of input to output prices. Instead, the degree of pass-through is dictated by the underlying market and demand structures, which I do not concretely specify as this approach is consistent with any degree of pass-through.

3.3.3.2 Unobserved productivity and identifying moments

To address endogeneity concerns resulting from the dependence of firms' flexible input decision on unobserved productivity, I employ a productivity control function approach in the spirit of Olley & Pakes (1996) and Levinsohn & Petrin (2003). I base my control function on firms' consumption of energy and raw materials, e_{it}, which are components of total intermediate inputs. Inverting the demand function for e_{it} gives an expression for productivity:

(3.8) $$\omega_{it} \equiv g_{it}(.) = g_{it}(e_{it}, k_{it}, l_{it}, \boldsymbol{z}_{it}),$$

where, in addition to k_{it} and l_{it}, $\boldsymbol{z}_{it}$ captures other state variables of the firm. Ideally, $\boldsymbol{z}_{it}$ should include a broad set of variables affecting productivity and demand for e_{it}. Therefore, I include dummy variables for export as well as research and development activities, firm-level import competition (as defined in section 3.2), the number of products a firm produces and the average wage it pays into $\boldsymbol{z}_{it}$. This specification allows for learning and competition effects from export market participation, import competition, and research activities as well as for (dis)economies of scope to influence firm productivity. Moreover, including wages in the control function for productivity absorbs unobserved quality and price differences that shift demand for e_{it} which accounts for the criticism of Gandhi, Navarro, & Rivers (2017) (De Loecker & Scott (2016)). Assuming that productivity evolves according to a first order Markov process, i.e. $\omega_{it} = \omega_{it-1} + \xi_{it}$, with ξ_{it} being the innovation in productivity, and plugging (3.7) and (3.8) into (3.6) gives:

$$q_{it} = \widetilde{\boldsymbol{\phi}}'_{it}\boldsymbol{\beta} + B_{it}(.) + g_{it-1}(.) + \varepsilon_{it} + \xi_{it}, \tag{3.9}$$

which constitutes the basis of my estimation.[41] I estimate (3.9) separately for every two-digit industry by using a one-step estimator in the spirit of Wooldridge (2009). I jointly form identifying moments on $\varepsilon_{it} + \xi_{it}$:

$$E\big((\varepsilon_{it} + \xi_{it})\boldsymbol{\Upsilon}_{it}\big) = 0, \tag{3.10}$$

where $\boldsymbol{\Upsilon}_{it}$ includes lagged interactions of intermediate inputs with capital and labor, contemporary interactions of capital and labor, lagged elements of $g_{it}(.)$, contemporary location and industry dummies, the lagged output price index, lagged market shares, as well as lagged interactions of the output price index with production inputs. By relying on those moments, I assume that output prices can react to productivity shocks but are correlated over time. Contrary, decisions about location, product mix, and exit and entry into export and research activities are quasi-fixed variables. This allows for the existence of sunk costs when entering export markets, building new plants, or designing new blueprints.

3.4 Empirical results

This chapter presents the empirical results. Section 3.4.1 discusses descriptive evidence on the degree of labor market distortions within the German manufacturing sector. Section 3.4.2 presents the main findings of this article, documenting how trade affects labor market distortions. Section 3.4.3 continues by analyzing the mechanisms underlying those results.

[41] I approximate $g_{it}(.)$ with a third order polynomial in all of its elements, except for the variables in $\boldsymbol{z}_{it}$. Those I add linearly. $B_{it}(.)$ is approximated with a flexible polynomial where I 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. This implementation is similar to the one in De Loecker et al. (2016).

3.4.1 Labor market distortions in the German manufacturing sector

TABLE 3.1

MEDIAN OUTPUT ELASTICITIES, BY SECTOR

Sector	Number of observations (1)	Intermediate inputs (2)	Labor (3)	Capital (4)	Returns to scale (5)
15 Food products and beverages	24,053	0.63	0.10	0.16	0.89
17 Textiles	5,909	0.67	0.30	0.17	1.14
18 Apparel, dressing, and dyeing of fur	1,941	0.74	0.21	0.15	1.07
19 Leather and leather products	1,328	0.63	0.20	0.03	0.88
20 Wood and wood products	5,140	0.64	0.24	0.08	0.99
21 Pulp, paper, and paper products	4,976	0.70	0.28	0.07	1.02
22 Publishing and printing	4,747	0.46	0.15	0.38	1.09
24 Chemicals and chemical products	11,632	0.70	0.25	0.12	1.07
25 Rubber and plastic products	11,471	0.67	0.25	0.07	0.99
26 Other non-metallic mineral products	9,568	0.66	0.32	0.10	1.10
27 Basic metals	7,115	0.68	0.31	0.05	1.02
28 Fabricated metal products	23,870	0.59	0.31	0.12	1.00
29 Machinery and equipment	28,224	0.61	0.37	0.08	1.05
30 Electrical and optical equipment	1,433	0.58	0.32	0.07	0.93
31 Electrical machinery and apparatus	10,402	0.61	0.32	0.10	1.01
32 Radio, television, and communication	3,030	0.66	0.32	0.15	1.09
33 Medical and precision instruments	7,894	0.59	0.27	0.19	1.07
34 Motor vehicles and trailers	6,710	0.68	0.31	0.26	1.27
35 Transport equipment	2,939	0.64	0.31	0.09	1.09
36 Furniture manufacturing	8,002	0.65	0.28	0.05	0.96
Across all industries	180,384	0.63	0.28	0.10	1.01

Notes: Table 3.1 reports median output elasticities from estimating the production function (3.9) for every NACE rev. 1.1 2-digit industry with sufficient observations. Column 1 reports the number of observations used to calculate output elasticities for each industry. Columns 2-4 respectively report median output elasticities for intermediate, labor, and capital inputs. Column 5 reports median returns to scale. All regressions control for time dummies and are weighted using population weights.

Table 3.1 presents median output elasticities for capital, labor, and intermediate inputs from estimating the production function (3.9) separately for every NACE rev. 1.1 two-digit industry with sufficient observations. Industry-level returns to scale range from 0.88 (leather and leather products) to 1.27 (motor vehicles and trailers) with having an overall median value of 1.01 (column 5). Output elasticities vary markedly between industries, which emphasizes the importance of allowing for technology differences across sectors. Overall, median output elasticities for intermediate, labor, and, capital inputs respectively equal 0.63, 0.28, and 0.10 (columns 2-5).

From the estimated output elasticities, I calculate labor market distortion parameters using equation (3.5). Table 3.2 documents industry-specific median values for δ_{it}^{L}, its absolute value, average yearly person wages, and the difference between the firm markup expressions calculated from firms' intermediate (μ_{it}^{M}) and labor (μ_{it}^{L}) input decision using the approach by De Loecker & Warzynski (2012).[42] The latter difference is included as it is frequently used as measure of labor market distortions in the literature and implies the value of δ_{it}^{L} (see Dobbelaere & Mairesse (2013) and subsequent work). Across all industries, the median firm pays a wage that, given its employment decision, is 4,400 euros above the output contribution of its employees (column 1). Relating this figure to observed wages, one finds that median distortions equal to $\frac{4{,}377*100}{36{,}513.61} \approx 12\%$ of paid wages. Across industries, labor market power levels vary enormously. Intuitively, one would expect that industries characterized by high wages and which manufacture technologically sophisticated products feature a strong workforce. Whereas this intuition holds for several industries (e.g. medical and precision instruments), high values of δ_{it}^{L} are not always associated with high wages (e.g. food products and beverages). This illustrates how labor market power on side of the employees can also emerge from a low output contribution given paid wages. In such a scenario, employees' labor market power could result from adjustment barriers that protect unproductive workers from being dismissed (e.g. long-term contracts).[43]

Column 2 shows the degree of absolute labor market distortions which reflects the total extent of labor market inefficiencies. Whereas the publishing and printing industry displays

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[42] The formulas for those firm-level markup expressions are: $\mu_{it}^{M} = \theta_{it}^{M} * \frac{P_{it}Q_{it}}{V_{it}^{M}M_{it}}$ and $\mu_{it}^{L} = \theta_{it}^{L} * \frac{P_{it}Q_{it}}{V_{it}^{L}L_{it}}$. I do not use the markup correction formula of De Loecker and Warzynski (2012), as this decreases my observation count and leads to similar markup differences. For more details on the sample firms' characteristics see Appendix B.1.

[43] In unreported statistics, I also find clearly higher median values of δ_{it}^{L} for West-German (5,410 euros) compared to East-German (excluding Berlin) firms (375 euros). This is consistent with the common perception that West-German employees possess higher levels of labor market power.

the largest absolute distortions, the most efficient labor market is found in the wood and wood products industry. However, even there, median distorted rents equal to 6,750 euros per full-time worker.

Table 3.2

SAMPLE MEDIANS FOR LABOR MARKET DISTORTIONS AND FIRM WAGES, BY SECTOR

Sector	δ_{it}^{L} (1)	$\lvert\delta_{it}^{L}\rvert$ (2)	V_{it}^{L} (3)	$\mu_{it}^{M}-\mu_{it}^{L}$ (4)	Observations (5)
15 Food products and beverages	12,490.55	12,502.39	24,491.73	0.50	18,032
17 Textiles	11.18	8,851.34	31,649.82	0.00	5,776
18 Apparel, dressing, and dyeing of fur	4,764.42	8,821.64	29,988.74	0.19	1,766
19 Leather and leather products	8,864.17	9,793.85	26,980.73	0.37	985
20 Wood and wood products	1,412.29	6,757.43	31,496.06	0.04	4,741
21 Pulp, paper, and paper products	-6,820.90	12,525.86	38,609.97	-0.20	4,107
22 Publishing and printing	-7,216.08	21,568.79	37,519.39	-0.15	1,483
24 Chemicals and chemical products	-1,952.28	11,449.42	46,002.97	-0.05	11,483
25 Rubber and plastic products	5,573.45	6,786.98	34,614.76	0.17	11,212
26 Other non-metallic mineral products	-2,864.04	9,697.13	36,840.28	-0.09	8,951
27 Basic metals	-3,910.66	12,431.88	40,957.17	-0.10	5,888
28 Fabricated metal products	5,383.92	11,035.70	36,124.81	0.18	23,667
29 Machinery and equipment	1,735.73	12,585.09	42,265.03	0.05	27,801
30 Electrical and optical equipment	-141.15	17,395.99	41,148.26	0.00	804
31 Electrical machinery and apparatus	1,344.55	12,730.50	37,315.81	0.04	10,127
32 Radio, television, and communication	3,847.69	16,105.19	35,565.13	0.14	2,382
33 Medical and precision instruments	13,500.65	16,843.87	38,153.71	0.47	7,513
34 Motor vehicles and trailers	-1,009.48	20,230.48	37,436.22	-0.03	5,393
35 Transport equipment	6,260.02	17,048.74	38,506.50	0.19	2,004
36 Furniture manufacturing	6,406.75	7,697.29	30,343.89	0.24	5,726
Across all industries	4,377.00	11,431.60	36,513.61	0.14	159,821

Notes: Table 3.2 reports sample medians of labor market distortions for every NACE rev. 1.1 2-digit industry. Column 1-4 respectively report medians for the labor market distortion parameter, its absolute value, average yearly person wages, and differences between De Loecker-Warzynski (2012) markups based on firms' intermediate and labor input decision. Column 5 reports the number of observations used to calculate the respective variables. The top and bottom one percent of observations with respect to the distribution of the labor market power parameter are excluded.

In some industries, the implied distortions are equivalent to 30-50% of overall wages. A substantial number that is concealed in existing measures based on subtracting μ_{it}^{M} and μ_{it}^{L} from each other. Notably, the differences between μ_{it}^{M} and μ_{it}^{L} that I estimate, and which imply the degree of labor market distortions, are smaller than documented in the literature.[44] Consequently, the monetary labor market distortions reported in Table 2 are *small* compared

[44] See Dobbelaere, Kiyota, & Mairesse 2015 who find values between -0.69 and 0.91, -0.29 and 0.76, and -2.57 and 0.91 respectively for France, Japan, and The Netherlands, Dobbelaere et al. (2016) finding values between -2.25 and 1.93 and -0.23 and 1.05 respectively for Chile and France, and Dobbelaere & Mairesse 2013 finding values between -1.10 and 0.50 for France.

to existing estimates. Judging from the pure magnitude of the estimated wage gaps, models featuring a bargaining over wages subsequent to a perfectly flexible labor quantity decision of the firm cannot explain those massive distortions. Instead, it is more consistent with the data that distortions emerge from various frictions, including the presence of wage bargaining power but also adjustment barriers to labor. Thus, a reduction of labor market inefficiencies can either be achieved through changes in firms' size, i.e. firms' marginal product of labor, or wages. International trade can affect both channels.

In my empirical exercise I run separate regressions for firms with ($\delta_{it}^{L} < 0$) and without ($\delta_{it}^{L} > 0$) labor market power, as the prevalence of labor market power distortions might determine how firms pass-through profit gains and losses from trade into wage and employment adjustments. Table 3.3 shows the sample percentages of firms characterized by $\delta_{it}^{L} > 0$ and $\delta_{it}^{L} < 0$, which I respectively denote as positively distorted (PD-) and negatively distorted (ND-) firms. Whereas some industries are dominated by one firm type (e.g. industry 15), other industries show a balanced population of PD- and ND-firms (e.g. industries 17, 20, 30). Thirteen out of twenty industries host a majority of PD-firms, whereas the other seven are dominated by ND-firms. In total, I classify 61.3 (38.7) percent of my firm-year observations as PD-firms (ND-firms).[45] Notably, within firms, the classification into PD- and ND-firms is stable across time. Only 7.7% of all observations switch between both categories.

[45] I abstain from using statistical tests for my classification as this involves arbitrary and normative decisions on when to classify a distortion as being compatible with perfect competition. Yet, even when I define a comparably large interval of $\delta_{it}^{L} \in [1500€, -1500€]$ as indicating perfect labor markets, the general scheme of my classification results remains unchanged. Using this definition, I classify 57.8%, 35.5%, and 6.7% of firms respectively into PD-firms, ND-firms, and firms active in perfectly competitive labor markets. My empirical results are unaffected when using this alternative classification scheme.

Table 3.3

SAMPLE PERCENTAGE OF FIRMS WITH
POSITIVE AND NEGATIVE LABOR MARKET DISTORTION PARAMETERS, BY SECTOR

Sector	Percentage of firm-year observations with $\delta_{it}^L >$ 0 (PD-firms) (1)	Percentage of firm-year observations with $\delta_{it}^L < 0$ (ND-firms) (2)	Number of firm-year observations (3)
15 Food products and beverages	96.48	3.52	18,520
17 Textiles	50.12	49.88	5,782
18 Apparel, dressing, and dyeing of fur	69.16	30.84	1,767
19 Leather and leather products	80.91	19.09	985
20 Wood and wood products	55.49	44.51	4,759
21 Pulp, paper, and paper products	33.60	66.40	4,217
22 Publishing and printing	40.06	59.94	1,680
24 Chemicals and chemical products	45.44	54.56	11,581
25 Rubber and plastic products	76.49	23.51	11,277
26 Other non-metallic mineral products	42.30	57.70	8,967
27 Basic metals	41.12	58.88	5,954
28 Fabricated metal products	64.86	35.14	23,805
29 Machinery and equipment	53.66	46.34	28,209
30 Electrical and optical equipment	47.52	52.48	909
31 Electrical machinery and apparatus	52.86	47.14	10,260
32 Radio, television, and communication	55.65	44.35	2,681
33 Medical and precision instruments	78.17	21.83	7,764
34 Motor vehicles and trailers	44.39	55.61	6,096
35 Transport equipment	58.31	41.69	2,099
36 Furniture manufacturing	76.88	23.12	5,769
Across all industries	61.32	38.68	163,081

Notes: Table 3.3 reports sample percentages PD-firms and ND-firms for every NACE rev. 1.1 two-digit industry. Columns 1-2 respectively report the sample percentages of PD-firms and ND-firms for each two-digit industry. Column 3 reports the associated number of sample observations per industry.

To show how PD- and ND-firms differ in their characteristics, I estimate the following equation by OLS:

(3.11)
$$\ln y_{it} = \gamma_0 + \gamma_i PD_{it} + \upsilon_j + \upsilon_t,$$

where PD_{it} is a dummy for being a PD-firm. υ_j and υ_t capture industry and time fixed effects. y_{it} can be any variable of interest. Table 3.4 shows results from estimating (3.11) using the logs of firms' wages, FTE, produced output, product market power ($\mu_{it}^M = \theta_{it}^M \frac{P_{it}Q_{it}}{V_{it}^M M_{it}}$), capital per labor ratios, and value-added per FTE as dependent variables.[46] Those variables give an intuition about the performance, size and, wage differences between

[46] I use μ_{it}^M as a measure of firms' product market power as μ_{it}^L captures labor market distortions in addition to firms' product market power.

PD- and ND-firms, which may be relevant in explaining labor market power structures. I stress that Table 3.4 does not intend to present causal evidence. After eliminating industry- and time-specific effects, I find that, on average, PD-firms pay higher wages, are smaller, both in terms of labor force and produced output, have higher product market power, display a lower labor productivity, and have lower capital to labor ratios.

Table 3.4

DIFFERENCES BETWEEN PD- AND ND-FIRMS

	Wages (1)	FTE (2)	Output (3)	Product market power (4)	Capital per FTE (5)	Value-added per FTE (6)
PD_{it}	0.0573***	-0.964***	-1.289***	0.169***	-0.473***	-0.0568***
	(0.00465)	(0.0145)	(0.0189)	(0.00305)	(0.0117)	(0.00947)
Industry FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
Observations	146.327	146.327	146.327	146.327	146.327	146.327
R-squared	0.274	0.239	0.274	0.264	0.161	0.061
Number of firms	31,942	31,942	31,942	31,942	31,942	31,942

Notes: Table 3.4 reports results from estimating equation (3.11) by OLS. The dependent variables in columns 1-6 respectively are the logs of firm-level wages, FTE, produced quantity, markups, capital per FTE, and value-added per FTE. All regressions include time and industry fixed effects and are weighted using population weights. Standard errors are clustered at the firm level. The top and bottom one percent of observations with respect to the distribution of the labor market distortion parameter are excluded. Significance: *10 percent, **5 percent, ***1 percent.

Intuitively, higher profits strengthen incentives for employees to bargain for a share of firms' rents (Nickell (1999)). Therefore, it is not surprising to find that PD-firms possess higher product market power levels and pay higher wages at the same time. Although PD-firms constitute the larger share of firms across most industries, ND-firms employ more workers. The share of workers with labor market power is thus lower than suggested from industry-level evidence. Generally, the results documented in Table 3.4 are consistent with the notion that firms with labor market power are typically large and highly productive "superstar" firms that dominate local labor markets.

3.4.2 International trade and labor market distortions

To infer on the effect of international trade on labor market distortions, I consider the following specification:

$$y_{it} = \gamma_{IMP} IMP_{it-1}^{CHN} + \gamma_{EXP} EXP_{it-1}^{CHN} + \boldsymbol{C}'_{it-1}\boldsymbol{\gamma} + \upsilon_{ij} + \upsilon_t \,, \tag{3.12}$$

where EXP_{it-1}^{CHN} and IMP_{it-1}^{CHN} respectively measure firm-level export opportunities to and import competition from China in period $t-1$. The vector $\boldsymbol{C}$ introduces control variables.[47] υ_t and υ_{ij} respectively capture time and firm times industry fixed effects, whereas $y_{it} = \{\delta_{it}^L, |\delta_{it}^L|\}$. Estimating the model in levels while controlling for firm fixed effects uses the same identifying variation as a first difference model but avoids a disproportional loss of observations when working with an unbalanced panel (as I do).

Table 3.5 displays results showing how international trade affects labor market distortions. Columns 1-4 start with OLS regressions, which imply that exposure to import competition *decreases* firms' labor market power (δ_{it}^L rises). Simultaneously, OLS-regressions show an increase in labor market efficiency from import competition ($\left|\delta_{it}^L\right|$ falls). According to OLS, export opportunities do not affect labor market power distortions.

For identifying the effects of international trade on labor market distortions, it is important that the competitiveness of intermediate inputs markets does not itself react to trade exposure. In columns 3 and 4 I account for those concerns by controlling for contemporaneous values of μ_{it}^M. This isolates responses of δ_{it}^L and $\left|\delta_{it}^L\right|$ from reactions of intermediate input markets and ensures that reported coefficients on γ_{IMP} and γ_{EXP} are not caused by changes in the

[47] I control for firms' worker outsourcing rate (costs for temporary agency workers over costs for temporary agency workers plus costs for permanently employed workers), labor productivity (the log of value-added over FTE), firms' share of researchers in their FTE, market share (a revenue weighted aggregation of firms' domestic product market shares) and FTE.

competitive benchmark (because μ_{it}^{M} reflects the wedge between the intermediate input output elasticity and the share of intermediate input expenditures in profits). However, changes in firms' product market power could itself influence rent sharing processes between employees and firms (Nickell (1999)). Thus, controlling for μ_{it}^{M} absorbs the part of the effect from international trade on δ_{it}^{L}, which works through changes in firms' product market power. When interpreting my results, I therefore focus on specifications that do not control for μ_{it}^{M} and consider specifications including μ_{it}^{M} as robustness checks. Yet, controlling for μ_{it}^{M} leaves the results unchanged.

Table 3.5

LABOR MARKET DISTORTIONS AND TRADE

	OLS				IV			
	δ_{it}^{L} (1)	$\lvert\delta_{it}^{L}\rvert$ (2)	δ_{it}^{L} (3)	$\lvert\delta_{it}^{L}\rvert$ (4)	δ_{it}^{L} (5)	$\lvert\delta_{it}^{L}\rvert$ (6)	δ_{it}^{L} (7)	$\lvert\delta_{it}^{L}\rvert$ (8)
IMP_{it-1}^{CHN}	99.06***	-39.83**	85.96***	-42.22**	220.30***	-43.98	187.60***	-49.91
	(26.28)	(18.53)	(23.84)	(18.35)	(61.31)	(42.94)	(53.46)	(43.40)
EXP_{it-1}^{CHN}	-15.98	29.79	-29.15	27.39	-413.90***	256.90***	-379.40***	263.10***
	(23.66)	(20.89)	(22.29)	(20.89)	(128.30)	(97.47)	(114.60)	(97.40)
μ_{it}^{M}	-	-	21,315***	3,895***	-	-	21,334***	3,873***
			(705.20)	(599.60)			(706.50)	(600.10)
Firm x Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES
Firm level controls	YES	YES	YES	YES	YES	YES	YES	YES
Observations	108,904	108,904	108,904	108,904	108,904	108,904	108,904	108,904
R-squared	0.921	0.864	0.930	0.865	0.920	0.864	0.930	0.864
First-stage F-test	-	-	-	-	108.9	108.9	108.9	108.9
Number of firms	24,334	24,334	24,334	24,334	24,334	24,334	24,334	24,334

Notes: Table 3.5 reports results from estimating equation (3.12) by OLS and IV using the full sample of firms. OLS-results are reported in columns 1-4. IV-results are reported in columns 5-8. The dependent variable in columns 1, 3, 5, and 7 is the labor market distortions parameter, δ_{it}^{L}, whereas in columns 2, 4, 6, and 8 it is the absolute value of the labor market distortion parameter, $\lvert\delta_{it}^{L}\rvert$. All regressions include time and industry times firm fixed effects and controls for firms' size, worker outsourcing rate, share of researchers in the entire workforce, market share, and labor productivity. All regressions are weighted using population weights. Standard errors are clustered at the firm level. The top and bottom one percent of observations with respect to the distribution of the labor market distortion parameter are excluded. Significance: *10 percent, **5 percent, ***1 percent.

As OLS might suffer from an endogeneity bias, causal inference from OLS-regressions is not possible. The main concern is that unobserved product demand and supply shocks simultaneously affect trade flows and domestic firms' labor demand.[48] To solve this identification problem, I apply an IV approach using trade flows between China and countries similar to Germany as instruments for IMP_{it}^{CHN} and EXP_{it}^{CHN}. I define instruments in the following way: For every product, I calculate the share of imports (exports) flowing from China (instrument group countries) to instrument group countries (China) in total imports (exports) flowing from the world (instrument group countries) to the instrument group countries (world).[49] Identical to the construction of IMP_{it}^{CHN} and EXP_{it}^{CHN}, I aggregate those product-level trade flows to the firm level by using product revenue shares in firms' total product market revenue.

Using trade flows to other countries as instruments for local trade flows exploits that China's rise induces demand and supply shocks also for other trade partners. When defining the instruments, I only use countries that are neither direct neighbors of Germany nor share the same currency. This minimizes concerns about correlated unobserved demand and supply shocks between Germany and countries included in the instrument group that would invalidate my identification (Dauth et al. (2014)).[50] Appendix B.7 reports the first stage regressions for the following main IV-results.

Using IV-estimators increases the magnitude of nearly all coefficients. According to column 5, a unit increase in import competition raises the share of rents that every full-time worker can capture from their firm relative to its output contribution by 220 euros, whereas a

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[48] There are several mechanisms that create an endogeneity problem in line with the results reported in Table 3.5. For instance, an unobserved domestic product supply shock, e.g. through government subsidies, could simultaneously lead to an increase in domestic firms' labor demand (which raises δ_{it}^{L}), a decrease in imports, and an increase in the capabilities of domestic firms to export. In that case, OLS coefficients for the effect of IMP_{it-1}^{CHN} and EXP_{it-1}^{CHN} on δ_{it}^{L} are respectively negatively and positively biased. Unobserved demand shocks can confound the OLS estimates in a comparable way. For further discussion please see Dauth et al. (2014).

[49] Formally, the product-level instruments for export opportunities and import competition are defined as: $EX_{gt}^{INS} = \frac{E_{gt}^{INS\rightarrow CHN}}{E_{gt}^{INS\rightarrow WORLD}} * 100$ and $IM_{gt}^{INS} = \frac{M_{gt}^{CHN\rightarrow INS}}{M_{gt}^{WORLD\rightarrow INS}} * 100$.

[50] The instrument country group includes Australia, New Zealand, Sweden, Norway, Japan, Great Britain, Canada, and Singapore (results are robust to different country specifications).

unit increase in export opportunities decreases this share by 414 euros. To put this into perspective: Using weights I calculate that throughout my observation period, Chinese import competition and export demand increased by 0.8 and 1.0 points, respectively. Furthermore, I calculate that every year roughly 5 million full-time workers are active in German manufacturing sector firms with at least 20 employees. Hence, the estimates in column 5 suggest that the increase in export demand (import competition) from China raised rents that surviving firms (workers in surviving firms) can capture, relative to their employees (firms) by 2.07 billion (880 million) euros.

The increase of δ_{it}^{L} from import competition is not associated with a statistically significant effect on labor market efficiency (column 6). In contrast, export demand shocks decrease labor market efficiency, implying that international trade, due to export participation of firms, can widen gaps between realized and potential output.[51] Nevertheless, export demand shocks may still be welfare increasing by raising profits on domestic products and/or exerting productivity enhancing effects (e.g. De Loecker 2013). The point is that a widening of gaps between wages and marginal products of labor implies a lower level of labor market efficiency compared to the first best scenario that is usually considered in theoretical trade models. Again, all results are robust to including μ_{it}^{M} as a control variable.

At first glance, my results might seem counterintuitive. Typically, one would expect that a rise in import competition would decrease δ_{it}^{L} by lowering employees' bargaining power due to a replacement of domestic production by foreign firms (Rodrik (1997)). By the reverse mechanism one could expect an increase of δ_{it}^{L} from new export opportunities. However, there is a simple intuition for a mechanism working against this logic: Final product trade may increase or decrease firms' profits stronger than their labor expenditures. Intuitively, the

[51] As expected, only exporting firms are affected by new export opportunities (results are available on request).

degree of pass-through from profit changes to workforce adjustment may be determined by existing distortions (existing levels of δ_{it}^{L}) that prevent smooth workforce adjustments.

To shed light on that, I first investigate whether prevalent labor market distortions interact with final product trade, leading to heterogeneous responses of δ_{it}^{L} for firms with (ND-firms) and without (PD-firms) labor market power. ND-firms could exploit their labor market power to prevent new export market profit gains from being shared with their workforce, decreasing δ_{it}^{L} for those firms. Oppositely, employees with positive labor market power might prevent output losses from import competition from being transferred to them. Note that such heterogeneities would exclude a significant role of short run adjustment frictions faced by all firms equally in driving the results. This is because one would expect that physical adjustment barriers (e.g. creating a job posting in response to an unexpected shock) would affect ND- and PD-firms equally. To further understand the underlying mechanisms, I subsequently analyze PD- and ND-firms' adjustment processes to trade exposure in the next section.

Table 3.6 runs the regressions from Table 3.5 again on firms grouped according to their $t-1$ regime-type. Within PD-firms, a one unit increase in import competition increases the share of rents that workers can gain relative to their firm by 130 euros (column 5). For ND-firms that coefficient is larger (232 euros). Consistent with those findings, labor market efficiency decreases (increases) from import competition targeted at PD-firms (ND-firms). However, for ND-firms, controlling for μ_{it}^{M} reduces the significance of those results to the 10-percent level (column 7 and 8). Compared to OLS-results, IV-estimators dramatically change the quantitative effect of export opportunities on δ_{it}^{L} within ND-firms: A one unit increase in export opportunities increases firms' rents, relative to their workers, by 613 euros (per full-time worker). This translates into a huge loss in labor market efficiency that amounts to 5 percent of the median (absolute) labor market distortion across all industries (Table 3.2).

Interestingly, there is no effect of export opportunities on labor market distortions within PD-firms. Thus, as export opportunities increase ND-firms' labor market power without affecting δ_{it}^{L} in PD-firms, an increase in foreign demand tends to raise inequality in labor market power between workers employed in PD- and ND-firms. I investigate this further in Appendix B.5 and show that there indeed exists a positive causal relationship between industry-level dispersion in δ_{it}^{L} and industry-level export opportunities.

The findings of Table 3.6 confirm that existing labor market distortion structures are relevant for determining how international trade influences labor market distortions. As export opportunities (import competition) might increase existing labor market distortions when firms' (employees') possess labor market power, trade can widen gaps between potential and realized output. Import competition can, however, exert a labor market disciplining effect by decreasing ND-firms' market power on labor markets. Consequently, it depends on existing domestic labor market power structures whether trade can improve or worsen labor market distortions. This constitutes a novel margin of gains (losses) from trade. Although I cannot quantify such gains and losses within my partial equilibrium analysis, my findings highlight that models abstracting from interdependencies between labor market characteristics and trade might misjudge distributional outcomes and welfare gains from trade.

Table 3.6

LABOR MARKET DISTORTIONS AND TRADE, PD-FIRMS VS. ND-FIRMS

Panel A: PD-firms	PD-firms							
	OLS				IV			
	δ_{it}^L	$\lvert\delta_{it}^L\rvert$	δ_{it}^L	$\lvert\delta_{it}^L\rvert$	δ_{it}^L	$\lvert\delta_{it}^L\rvert$	δ_{it}^L	$\lvert\delta_{it}^L\rvert$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IMP_{it-1}^{CHN}	52.16**	45.21**	34.71*	30.88*	129.50***	107.50**	90.20**	75.27**
	(21.14)	(19.48)	(19.36)	(17.96)	(46.18)	(39.84)	(41.80)	(36.23)
EXP_{it-1}^{CHN}	-12.88	-12.59	-14.43	-13.87	-40.84	27.79	-67.70	5.741
	(26.25)	(21.99)	(23.32)	(19.63)	(121.90)	(97.89)	(112.00)	(89.53)
μ_{it}^M	-	-	15,385***	12,633***	-	-	15,374***	12,623***
			(420.90)	(358.30)			(421.10)	(358.40)
Firm ∗ Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES
Firm level controls	YES	YES	YES	YES	YES	YES	YES	YES
Observations	63,271	63,271	63,271	63,271	63,271	63,271	63,271	63,271
R-squared	0.833	0.846	0.858	0.865	0.833	0.846	0.857	0.865
First-stage F-test	-	-	-	-	73.16	73.16	73.14	72.14
Number of firms	16,493	16,493	16,493	16,493	16,493	16,493	16,493	16,493
Panel B: ND-firms	**ND-firms**							
	OLS				IV			
	δ_{it}^L	$\lvert\delta_{it}^L\rvert$	δ_{it}^L	$\lvert\delta_{it}^L\rvert$	δ_{it}^L	$\lvert\delta_{it}^L\rvert$	δ_{it}^L	$\lvert\delta_{it}^L\rvert$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IMP_{it-1}^{CHN}	183.40***	-164.40***	181.20***	-162.80***	231.90**	-211.60**	172.00*	-167.80*
	(50.01)	(48.84)	(49.23)	(50.05)	(117.50)	(106.30)	(103.50)	(99.23)
EXP_{it-1}^{CHN}	-40.25	46.61	-79.34*	75.15*	-612.80**	590.80***	-437.50**	462.70**
	(48.22)	(45.32)	(43.03)	(41.73)	(245.20)	(199.30)	(214.10)	(182.90)
μ_{it}^M	-	-	37,712***	-27,531***	-	-	37,807***	-27,634***
			(1,720)	(1,660)			(1,719)	(1,664)
Firm ∗ Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES
Firm level controls	YES	YES	YES	YES	YES	YES	YES	YES
Observations	41,301	41,301	41,301	41,301	41,301	41,301	41,301	41,301
R-squared	0.877	0.888	0.894	0.898	0.876	0.887	0.894	0.898
First-stage F-test	-	-	-	-	34.48	34.48	34.56	34.56
Number of firms	8,736	8,736	8,736	8,736	8,736	8,736	8,736	8,736

Notes: Table 3.6 reports results from estimating equation (3.12) by OLS and IV using separate samples for $t-1$ PD-firms and ND-firms, respectively reported in Panel A and Panel B. OLS-results are reported in columns 1-4. IV-results are reported in columns 5-8. The dependent variable in columns 1, 3, 5, and 7 is the labor market distortions parameter, δ_{it}^L, whereas in columns 2, 4, 6, and 8 it is the absolute value of the labor market distortions parameter, $|\delta_{it}^L|$. All regressions include time and industry times firm fixed effects and controls for firms' size, worker outsourcing rate, share of researchers in the entire workforce, market share, and labor productivity. Regressions are weighted using population weights. Standard errors are clustered at the firm level. The top and bottom one percent of observations with respect to the distribution of the labor market distortion parameter are excluded. Significance: *10 percent, **5 percent, ***1 percent.

3.4.3 Firm adjustment to international trade

Wedges between workers' output contribution and wages change, when, in response to increasing trade exposure, labor expenditure adjustments do not concord with changes in profits. This creates room for labor market disciplining and distorting effects from trade. So far, the evidence of this article suggests a domination of the latter in the case of Germany. Interestingly, incomplete adjustment processes on labor markets bear a close analogy to recent findings on an incomplete pass-through of trade related cost savings and exchange rate shocks to consumer prices (e.g. Amiti, Itskhoki, & Konings (2014); De Loecker et al. (2016)). Recent work highlights such incomplete pass-through processes in output markets as a source of distorting effects from international trade (e.g. Arkolakis et al. (2018); Weinberger (2017)). Similar to this literature on product market distortions, an incomplete pass-through from firm profit changes to labor input adjustments could introduce distortions on labor markets, explaining the previous section's results.

To investigate this further, Table 3.7 reports IV-regression results for the responses of firms' revenue deflated by an industry-level deflator (r_{it}), FTE (l_{it}), average wages (v_{it}^L), and ratio of intermediate to labor input expenditures (χ_{it}) – all in logs – to trade exposure. Results are separately reported for PD- (Panel A) and ND-firms (Panel B). Indeed, Table 3.7 suggests that trade related profit changes are not perfectly passed through into labor adjustments. Note, however, that the mechanism behind the effect of import competition on ND-firms cannot be fully identified. This is unsurprising, as the associated response of δ_{it}^L within ND-firms was only imprecisely estimated after controlling for the competitiveness of intermediate input markets. In contrast, for PD-firms I find a clear negative effect of import competition on revenues and employment. To understand the mechanism behind the previously reported positive effect of import competition on δ_{it}^L within PD-firms, note that PD-firms decrease intermediate input expenditures stronger than labor expenditures (column 4). Consequently, although employees in PD-firms suffer from adverse competition shocks, PD-firms cannot completely pass-through the negative effects into workforce adjustments, increasing δ_{it}^{L} for those firms. Hence, employees with positive labor market power are partly protected from adverse shocks, which creates allocative inefficiencies (i.e. PD-firms cannot shrink sufficiently).

Table 3.7

FIRM ADJUSTMENTS AND TRADE,
PD-FIRMS VS. ND-FIRMS

Panel A: PD-firms	PD-firms			
	r_{it} (1)	l_{it} (2)	v_{it}^{L} (3)	χ_{it} (4)
IMP_{it-1}^{CHN}	-0.0103***	-0.00803***	-0.000714	-0.00538***
	(0.00252)	(0.00206)	(0.000854)	(0.00195)
EXP_{it-1}^{CHN}	0.0259***	0.00910**	0.00955***	0.00617
	(0.00625)	(0.00436)	(0.00235)	(0.00460)
Firm $*$ Industry FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Observations	63,271	63,271	63,271	63,271
R-squared	0.982	0.981	0.939	0.940
First-stage F-test	73.23	73.23	73.23	73.23
Number of firms	16,493	16,493	16,493	16,493

Panel B: ND-firms	ND-firms			
	r_{it} (1)	l_{it} (2)	v_{it}^{L} (3)	χ_{it} (4)
IMP_{it-1}^{CHN}	0.00357	0.00208	0.00108	-0.00373
	(0.00436)	(0.00318)	(0.00213)	(0.00357)
EXP_{it-1}^{CHN}	0.0200***	0.000116	0.00265	0.0239***
	(0.00713)	(0.00581)	(0.00365)	(0.00734)
Firm $*$ Industry FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Observations	41,301	41,301	41,301	41,301
R-squared	0.986	0.986	0.955	0.926
First-stage F-test	34.42	34.42	34.42	34.42
Number of firms	8,736	8,736	8,736	8,736

Notes: Table 3.7 reports results from estimating equation (3.12) without any control variables by IV using separate samples for $t-1$ PD-firms and ND-firms, respectively reported Panel A and Panel B. The dependent variables in columns 1, 2, 3, and 4 respectively are logs of firms' revenue deflated with an industry specific price index, FTE, average wages, and ratio between intermediate and labor input expenditures. All regressions include time and industry times firm fixed effects and are weighted using population weights. Standard errors are clustered at the firm level. The top and bottom one percent of observations with respect to the distribution of the labor market distortion parameter are excluded. Significance: *10 percent, **5 percent, ***1 percent.

Within PD-firms, new rents from export market participation are passed-through into positive workforce adjustments. This explains the insignificant effects from export opportunities on δ_{it}^{L} and $|\delta_{it}^{L}|$ within PD-firms (labor input adjustments are in concordance with profitability changes). Astonishingly, ND-firms react differently. While ND-firms can increase their output in response to export demand shocks, they neither adjust their employment nor their wages upwards. However, ND-firms increase their intermediate input expenditures. This creates a wedge between adjustments in flexible commodities and labor input expenditures implying an incomplete pass-through of export profit gains to adjustments in labor expenses. Moreover, this could signal that ND-Firms can easily substitute workers for intermediate inputs, offering one possible (tentative) explanation for their strong position on labor markets. Exactly this ND-firms-specific mechanism gives rise to labor market distorting effects from export opportunities. Importantly, export opportunities lead to an increase in wages and employment within PD-firms, while *simultaneously* both variables are unaffected within ND-firms. This implies that the decrease in δ_{it}^{L} and the associated decrease in labor market efficiency from an increase in export opportunities for ND-firms are unlikely to be caused by institutional barriers or short run adjustment frictions preventing upward wage and employment adjustments.[52] Otherwise, PD-firms should be equally unable to adjust wages or employment upwards, which Table 3.7 disproves.

3.5 Robustness

This section provides robustness tests. In section 5.1 I rerun my entire estimation procedure without correcting for unobserved firm price variation. In section 5.2 I address

[52] Notably, I define labor inputs as FTE. Moreover, wages in AFiD also include bonus payments and "other social costs" like advanced training and company outings. Both variables should be less affected by short-run adjustment frictions compared to defining employment and wages in terms of headcounts and monthly salaries.

concerns about endogeneity with respect to my instruments by constructing new instruments that exclusively rely on firms' first observed product portfolio when aggregating product-level trade flows to the firm level. Nearly all of my findings are qualitatively robust to both tests. Beyond that, Appendix B.6 presents two additional robustness checks showing that my results are qualitatively unchanged when i) using the BRICS country group (Brazil, Russia, India, China, and South Africa) instead of China as Germany's trade partner and when ii) excluding firms which changed their classification into PD- and ND-firms between t and $t-1$.

3.5.1 Ignoring firm-level price variation

Table 3.8

LABOR MARKET DISTORTIONS AND TRADE WHEN IGNORING FIRM-LEVEL PRICE VARIATION

	All firms		PD-firms		ND-firms	
	δ_{it}^{L} (1)	$\lvert\delta_{it}^{L}\rvert$ (2)	δ_{it}^{L} (3)	$\lvert\delta_{it}^{L}\rvert$ (4)	δ_{it}^{L} (5)	$\lvert\delta_{it}^{L}\rvert$ (6)
IMP_{it-1}^{CHN}	179.10***	65.50*	133.00***	104.50**	17.30	14.48
	(49.00)	(33.79)	(46.19)	(43.87)	(79.34)	(65.31)
EXP_{it-1}^{CHN}	-331.00***	158.30	-61.42	-75.44	-595.10***	391.20**
	(115.30)	(99.47)	(123.30)	(116.40)	(213.80)	(188.00)
Firm $*$ Industry FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
Firm level controls	YES	YES	YES	YES	YES	YES
Observations	97,557	97,557	63,630	63,630	29,378	29,378
R-squared	0.922	0.856	0.851	0.861	0.856	0.868
First-stage F-test	86.77	86.77	48.82	48.82	26.22	26.22
Number of firms	22,546	22,546	16,428	16,428	6,776	6,776

Notes: Table 3.8 reports IV-results from estimating equation (3.12) after rerunning the entire estimation procedure without controlling for unobserved firm-level prices. Columns 1 and 2 report results for the full sample of firms. Columns 3 and 4 report results for $t-1$ PD-firms, whereas columns 5 and 6 report results for $t-1$ ND-firms. In columns 1, 3, and 5 the dependent variable is the labor market distortion parameter, δ_{it}^{L}, whereas in columns 2, 4, and 6 it is the absolute value of the labor market distortion parameter, $|\delta_{it}^{L}|$. All regressions include time and industry times firm fixed effects and controls for firm size, firms' worker outsourcing rate, firms' share of researchers in the entire workforce, firms' market share and firms' labor productivity. Regressions are weighted using population weights. Standard errors are clustered at the firm level. The top and bottom one percent of observations with respect to the distribution of the labor market distortion parameter are excluded. Significance: *10 percent, **5 percent, ***1 percent.

Table 3.8 reports results from estimating equation (3.12) by IV after rerunning my entire estimation procedure without controlling for unobserved firm-level prices, i.e. I omit average wages and variables in $B_{it}(.)$ from equation (3.9) and deflate firm revenues with an industry-level deflator. Table 3.8 first pools all firms (columns 1 and 2) and subsequently separates them into PD-firms (columns 3 and 4) and ND-firms (columns 5 and 6). Although controlling for unobserved firm price variation is important for determining levels of labor market power (see Appendix B.4), it is less important for estimating the responses of labor market distortions to trade exposure. Most of my results are qualitatively unchanged when I omit the firm-level price correction from my estimation procedure. The only exceptions are the previously negative effect of export opportunities on $|\delta_{it}^L|$ for the full sample of firms and the labor market disciplining effect of import competition on ND-firms that decreased those firms' labor market power and increased labor market efficiency. Again, export opportunities exert markedly stronger effects than import competition.

3.5.2 Endogeneity of firms' product portfolio

A potential threat to my identification is that firms could adjust their product portfolio in expectation of changes in China's supply and demand conditions, creating a self-selection problem. The product-level dimension of the AFiD data allows me to test for this potential identification threat. To do so, I construct time constant weights for every firm, based on firms' first product portfolio observed in the data. I use those weights to calculate new instruments, which ignore the channel of firms' product mix adjustment when identifying the responses of labor market distortions to trade. This procedure decreases the explaining power of my instruments, which should lead to a loss in terms of precision when using the new instruments.

Table 3.9 separately documents IV-results from using the new instruments for the full sample of firms as well as for PD- and ND-firms separately. Result reported in Table 3.9 are qualitatively similar to the baseline results (Tables 3.5 and 3.6). Like expected, standard errors go up when using the new weighting scheme. Yet, only the labor market disciplining effect from import competition, which decreased ND-firms labor market power becomes insignificant when using the new instruments. However, the size of the associated coefficients is roughly equal to the corresponding ones in Table 3.6, meaning that the increase in standard errors drives the insignificance. In all other cases, I receive roughly the same results as in my baseline specification, implying that endogenous product mix adjustment are no concern for my empirical strategy.

Table 3.9

LABOR MARKET DISTORTIONS AND TRADE, USING FIRST PORTFOLIOS FOR INSTRUMENTS

	All firms		PD-firms		ND-firms	
	δ_{it}^{L}	$\lvert\delta_{it}^{L}\rvert$	δ_{it}^{L}	$\lvert\delta_{it}^{L}\rvert$	δ_{it}^{L}	$\lvert\delta_{it}^{L}\rvert$
	(1)	(2)	(3)	(4)	(5)	(6)
IMP_{it-1}^{CHN}	203.20***	-26.98	142.20**	129.50**	226.00	-199.50
	(76.05)	(50.11)	(67.33)	(58.57)	(143.90)	(140.50)
EXP_{it-1}^{CHN}	-327.10*	286.90**	-59.05	42.39	-795.00**	715.40***
	(174.80)	(131.40)	(190.20)	(140.80)	(310.40)	(283.90)
Firm $*$ Industry FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
Firm level controls	YES	YES	YES	YES	YES	YES
Observations	100,815	100,815	58,527	58,527	38,228	38,228
R-squared	0.921	0.864	0.833	0.846	0.875	0.887
First-stage F-test	61.16	61.16	65.52	65.52	15.59	15.59
Number of firms	22,580	22,580	15,269	15,269	8,109	8,109

Notes: Table 3.9 reports results from estimating equation (3.12) by IV using weights from firms' first observed product portfolio when constructing firm-level instruments for trade shocks. Columns 1 and 2 report results for the full sample of firms. Columns 3 and 4 report results for $t-1$ PD-firms, whereas columns 5 and 6 report results for $t-1$ ND-firms. In columns 1, 3, and 5 the dependent variable is the labor market distortion parameter, δ_{it}^{L}, whereas in columns 2, 4, and 6 it is the absolute value of the labor market distortion parameter, $|\delta_{it}^{L}|$. All regressions include time and industry times firm fixed effects and controls for firm size, firms' worker outsourcing rate, firms' share of researchers in the entire workforce, firms' market share and firms' labor productivity. Regressions are weighted using population weights. Standard errors are clustered at the firm level. The top and bottom one percent of observations with respect to the distribution of the labor market distortion parameter are excluded. Significance: *10 percent, **5 percent, ***1 percent.

3.6 Conclusion

This article examines how international trade shapes and interacts with imperfections on labor markets by using a simple econometric partial equilibrium approach. I estimate labor market distortions by calculating monetary wedges between workers' output contribution and received compensation that prevent the competitive labor market outcome. The approach I present neither invokes a priori assumptions on the explicit form of labor market distortions nor models workers' outside options in wage bargaining games, as it recovers labor market distortions from observed differences between wages and marginal revenue products of labor.

In studying the impact of international trade on labor market imperfections in the German manufacturing sector, I find that firms possessing labor market power prevent an optimal pass-through of export profits gains to labor input expenditures. This raises their profit shares relative to their worker's labor shares. At the same time, firms facing a workforce with positive labor market power cannot fully pass-through losses from import competition into efficient wage and employment adjustments. Both effects distort rents towards firms and employees with labor market power and decrease total labor market efficiency. In contrast, evidence for labor market disciplining effects is extremely sensitive to the employed empirical specification.

The relevance of existing heterogeneous structures of labor market distortions in shaping distributional and efficiency related outcomes is an aspect that is widely unconsidered in theoretical models of trade. Yet, the result that international trade fortifies prevalent labor market distortions in most cases is of clear importance to the political architecture of trade agreements. Although trade may still be welfare increasing, an increase in labor market distortions from trade diminishes total trade gains compared to the first best allocative efficient scenario, which is usually considered in most theoretical models of international trade.

An important aspect that this article emphasizes is the role of imperfect functioning labor markets in increasing firms' labor market power by enabling an increase in profits without an associated increase in labor expenses. Theoretically, aggregate phenomena like declining labor shares or rising inequality could be similarly tied to imperfect functioning labor markets, on which specific actors exploit their labor market power to influence rent sharing processes. I believe that investigating this further constitutes a promising field for future research and I hope that this article lends itself helpful in encouraging fruitful discussions on those and related questions.

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Appendix B

B.1 Firm characteristics and the evolution of trade measures

TABLE B.1

SUMMARY STATISTICS FOR SAMPLE FIRMS

Variable	Mean (1)	Sd (2)	P25 (3)	Median (4)	P75 (5)	Observations (6)
Revenue in thousand Euros	50,500	258,000	4,828	11,600	34,500	159,821
Deflated capital stock in thousand Euros	31,600	166,000	2,109	5,981	19,700	159,821
Intermediate inputs in thousand Euros	33,300	183,000	2,560	6,810	21,700	159,821
Full time equivalent (FTE)	237.19	833.69	43.50	86.00	202.00	159,821
Total wage bill in thousand Euros	12,100	56,300	1,534	3,304	8,721	159,821
Firm level average nominal wage	41,248	13,399	31,654	40,454	49,662	159,821
Deflated capital over FTE	98,660	107,472	37,313	67,941	121,750	159,821
Log of real value-added over FTE	10.81	0.49	10.51	10.82	11.11	159,735
Log of firm price index	0.08	0.21	0	0.06	0.18	159,794
Log of revenue weighted sum of product market shares (revenue-based)	0.95	1.97	-0.38	1.08	2.47	159, 821
Log of revenue weighted sum of product market shares (quantity-based)	0.68	2.37	-0.88	0.95	2.54	130,462
Number of products	3.52	6.98	1	2	4	159,821
Dummy for export status	0.77	0.42	1	1	1	159,821
Dummy for R&D activities	0.34	0.47	0	0	1	159,821
Worker outsourcing rate	2.78	5.58	0	0.36	3.15	159,821
De Loecker-Warzynski (2012) Markup (intermediate input decision)	1.10	0.22	0.96	1.06	1.18	159,821
De Loecker-Warzynski (2012) Markup (labor input decision)	1.02	0.50	0.69	0.94	1.26	159,821
Labor market power parameter	127	21,240	-7,503	4,377	13,223	159,821
Absolute labor market power parameter	15,206	14,831	5,435	11,432	19,996	159,821
Import competition measure (firm level)	1.67	5.34	0	0.32	0.73	154,912
Export opportunity measure (firm level)	0.89	2.59	0	0.04	0.68	154,912

Notes: Table B.1 reports sample summary statistics for firms for which labor market distortions parameters can be calculated. 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. The top and bottom one percent of observations with respect to the distribution of the labor market distortion parameter are excluded.

Figure B.1 plots the evolution of my firm-level measures of Chinese import competition and German export opportunities to China for the entire observation period. In addition, Figure B.2 separates firms into PD- (left graph) and ND-firms (right graph). In both Figures, the blue solid and red dashed line respectively refers to the measure of import competition and export opportunities.

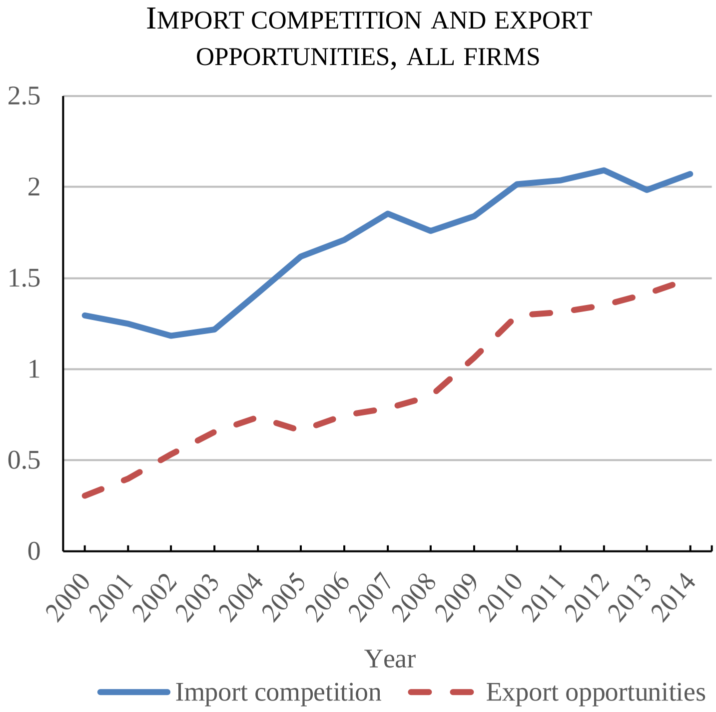

FIGURE B.1 – Evolution of firm-level import competition and export opportunity measures for all firms. Sample firms.

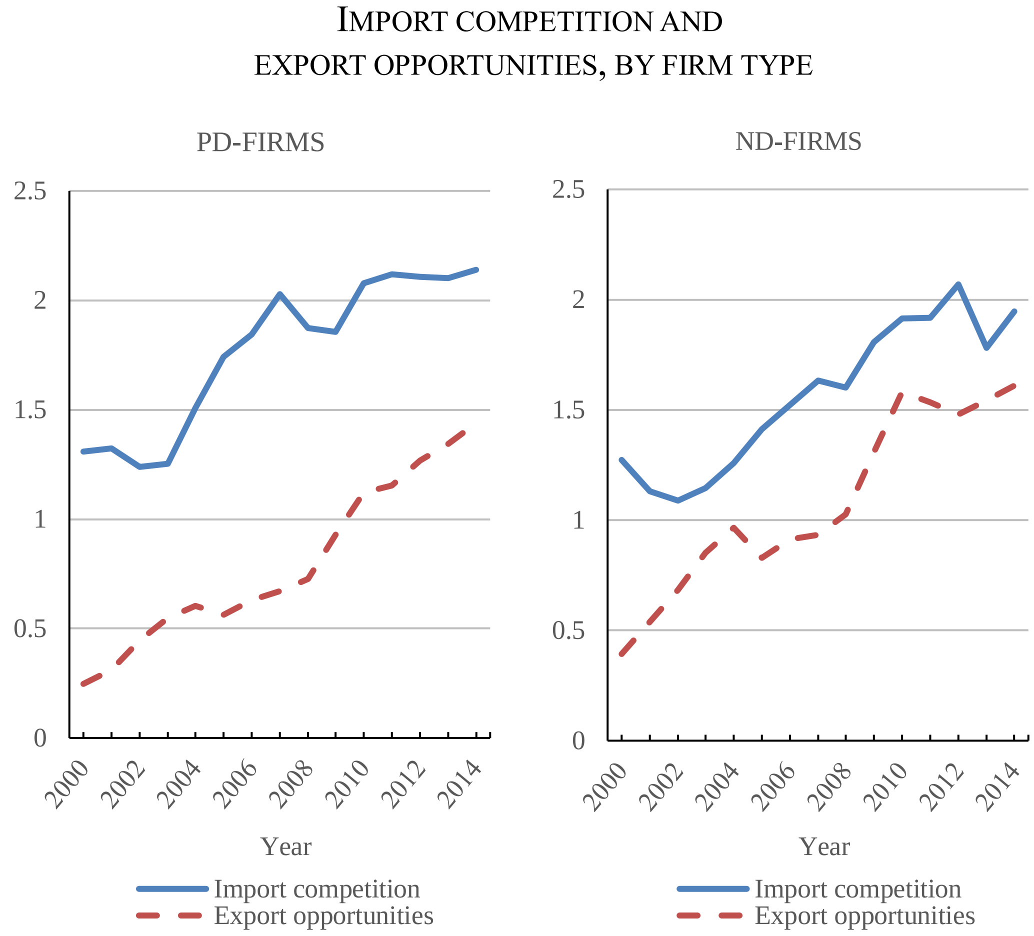

FIGURE B.2 – Evolution of firm-level import competition and export opportunity measures, separately for PD- and ND-firms. Sample firms.

B.2 Deriving a parameter for labor market distortions

In the following I first derive equation (3.5) form the main text and then discuss how this expression is linked to the framework of Dobbelaere & Mairesse (2013).

Distortions are given by:

(B.1) $$\delta_{it}^{L} = V_{it}^{L} - MRPL_{it} \, .$$

As intermediate input markets are competitive, it holds that: $V_{it}^{M} = MRPM_{it}$, with $MRPM_{it}$ being the marginal revenue product of intermediates. Using this, one can write:

(B.2) $$\delta_{it}^{L} = V_{it}^{L} - \frac{V_{it}^{M}}{MRPM_{it}} MRPL_{it} = V_{it}^{L} - \frac{V_{it}^{M}}{MPM_{it}} MPL_{it} \, .$$

Expanding the second term of (B.2) with $\frac{L_{it}}{Q_{it}} / \frac{L_{it}}{Q_{it}}$ and $\frac{M_{it}}{Q_{it}} / \frac{M_{it}}{Q_{it}}$ and noting that marginal products of labor (MPL_{it}) and intermediates (MPM_{it}) respectively are given by $\frac{\partial Q_{it}}{\partial L_{it}}$ and $\frac{\partial Q_{it}}{\partial M_{it}}$ allows us to rewrite (B.2) in the following way:

(B.3) $$\delta_{it}^{L} = V_{it}^{L} - \frac{V_{it}^{M} \frac{M_{it}}{Q_{it}}}{\frac{\partial Q_{it}}{\partial M_{it}} \frac{L_{it}}{Q_{it}} \frac{M_{it}}{Q_{it}}} \frac{\partial Q_{it}}{\partial L_{it}} \frac{L_{it}}{Q_{it}} \, .$$

This is the same as:

(B.4) $$\delta_{it}^{L} = V_{it}^{L} - \frac{\theta_{it}^{L}}{\theta_{it}^{M}} \frac{V_{it}^{M} M_{it}}{L_{it}} = \frac{V_{it}^{L} L_{it}}{L_{it}} - \frac{\theta_{it}^{L}}{\theta_{it}^{M}} \frac{V_{it}^{M} M_{it}}{L_{it}} \, ,$$

which is equal to equation (3.5) of the main text.

De Loecker & Warzynski (2012) and Dobbelaere & Kiyota (2018) show that one can derive an expression for firms' product market power from the firm's optimal input decision for any flexible input whose associated input market is also competitive. In my case, this would be the intermediate input market and the associated formula is given by:

(B.5) $$\mu_{it}^{M} = \frac{\partial Q_{it}(.)}{\partial M_{it}} \frac{M_{it}}{Q_{it}} * \frac{P_{it}Q_{it}}{V_{it}^{M} M_{it}}.$$

μ_{it}^{M} only captures true output market power of the firm because the intermediate input market is competitive. In contrast, when using the same expression for the labor input, μ_{it}^{L} also captures imperfections on labor markets as observed labor expenditures deviate from optimal labor expenditures. When expressing labor market distortions in monetary terms this can be highlighted as:

(B.6) $$\mu_{it}^{L} = \frac{\partial Q_{it}(.)}{\partial L_{it}} \frac{L_{it}}{Q_{it}} * \frac{P_{it}Q_{it}}{L_{it}} \frac{\partial Q_{it}(.)}{\partial L_{it}} \frac{L_{it}}{Q_{it}} * \frac{P_{it}Q_{it}}{(V_{it}^{L^*} + \delta_{it}^{L})L_{it}},$$

where observed wages, V_{it}^{L}, deviate from optimal wages, $V_{it}^{L^*} = MRPL_{it}$, by the degree of labor market distortions. Dobbelaere & Mairesse (2013) show that only if labor markets are as competitive as intermediate input markets ($\delta_{it}^{L} = 0$), it will hold that $\mu_{it}^{M} = \mu_{it}^{L}$. Dobbelaere & Mairesse (2013) further define that $\mu_{it}^{M} < \mu_{it}^{L}$ indicates a labor market regime where firms possess wage setting power (i.e. a monopsonistic labor market), whereas $\mu_{it}^{M} > \mu_{it}^{L}$ implies a efficient bargaining regime, where workers possess positive wage bargaining power.[53] Interestingly, reformulating the condition $\mu_{it}^{M} = \mu_{it}^{L}$ gives:

(B.7) $$\mu_{it}^{M} = \mu_{it}^{L} \quad if \;\; \delta_{it}^{L} = 0,$$

(B.8) $$\frac{\partial Q_{it}(.)}{\partial M_{it}} \frac{M_{it}}{Q_{it}} * \frac{P_{it}Q_{it}}{V_{it}^{M} M_{it}} = \frac{\partial Q_{it}(.)}{\partial L_{it}} \frac{L_{it}}{Q_{it}} * \frac{P_{it}Q_{it}}{\left(V_{it}^{L^*} + \delta_{it}^{L}\right)L_{it}} \quad if \;\; \delta_{it}^{L} = 0.$$

Using $V_{it}^{L^*} + \delta_{it}^{L} = V_{it}^{L}$ leads to:

[53] Originally, Dobbelaere & Mairesse (2013) apply this framework to the industry level. A firm level application can be found in Dobbelaere & Kiyota (2018).

$$(B.9) \qquad 0 = \delta_{it}^{L} = \frac{V_{it}^{L} L_{it}}{L_{it}} - \frac{\theta_{it}^{L}}{\theta_{it}^{M}} * \frac{V_{it}^{M} M_{it}}{L_{it}} = V_{it}^{L} - \frac{V_{it}^{M}}{MPM_{it}} MPL_{it} \qquad if \;\; \delta_{it}^{L} = 0.$$

Note that equation (B.9) is identical to equation (B.4) and equation (3.5) of the main text. In fact, it is immediately clear that it follows from $\delta_{it}^{L} > 0$, that $V_{it}^{L} > V_{it}^{L^*}$ and $\mu_{it}^{M} > \mu_{it}^{L}$ must hold. Consequently, classifying firms into monopsonistic and efficient bargaining regimes based on comparing μ_{it}^{L} and μ_{it}^{M} with each other (as in Dobbelaere & Mairesse (2013)) is identical to classifying firms based on comparing δ_{it}^{L} with zero. Finally, note also that larger differences between μ_{it}^{M} and μ_{it}^{L} imply larger values of δ_{it}^{L}, since:

$$(B.10) \qquad \delta_{it}^{L} = \frac{V_{it}^{L} L_{it}}{L_{it}} - \frac{\theta_{it}^{L}}{\theta_{it}^{M}} * \frac{V_{it}^{M} M_{it}}{L_{it}} \frac{\frac{P_{it} Q_{it}}{V_{it}^{L} L_{it}}}{\frac{P_{it} Q_{it}}{V_{it}^{L} L_{it}}} \frac{\frac{P_{it} Q_{it}}{V_{it}^{M} M_{it}}}{\frac{P_{it} Q_{it}}{V_{it}^{M} M_{it}}} = V_{it}^{L} - \frac{\mu_{it}^{L}}{\mu_{it}^{M}} V_{it}^{L}.$$

B.3 Dispersion of μ_{it}^{M} and μ_{it}^{L}

Using intermediate inputs as competitive benchmark might generate concerns about the plausibility of this assumption. For identification of the effects of international trade on labor market distortions within firms, it is especially important that the competitiveness of intermediate inputs markets does not vary over time. I address this in my empirical section. In the following I additionally show that μ_{it}^{M}, is less dispersed than μ_{it}^{L}. Figure B.3 shows the respective density plot for both expressions.

SAMPLE DISPERSION OF μ_{it}^{M} AND μ_{it}^{L} ACROSS ALL FIRMS

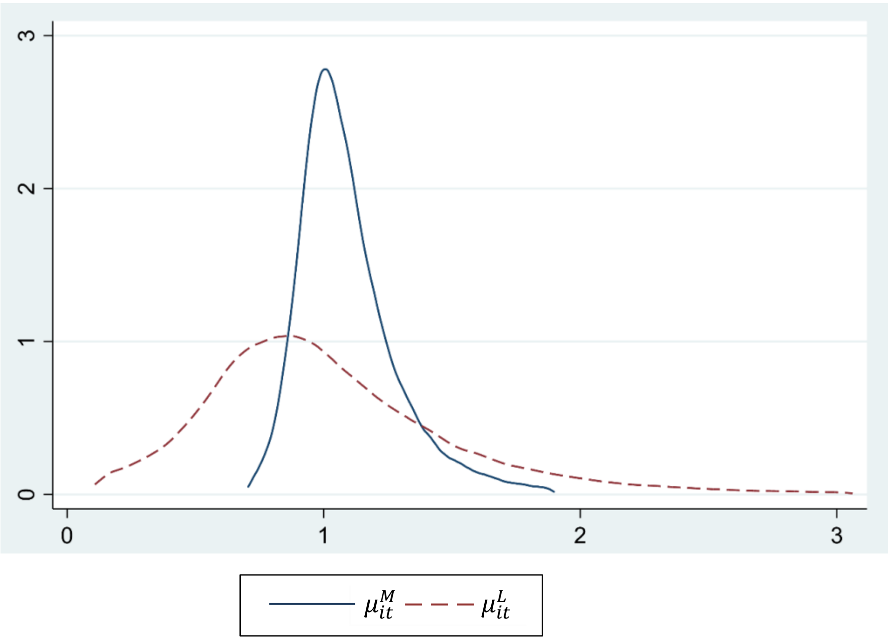

FIGURE B.3 – Kernel density plots for μ_{it}^{M} and μ_{it}^{L} across all sample firms. Outliers below and above the 1st and the 99th percentiles are trimmed.

Clearly, μ_{it}^{L} is more dispersed than μ_{it}^{M}, which is consistent with the idea that labor market distortions vary stronger than intermediate input market distortions. Moreover, whereas values for μ_{it}^{M} lie in an interval that is intuitively consistent with μ_{it}^{M} measuring true final product market power, μ_{it}^{L} displays values that are conflicting with the idea that μ_{it}^{L} is only measuring firms' output market power (the peak of the distribution of μ_{it}^{L} lies below unity). The extreme values of μ_{it}^{L} can only be rationalized when one considers that μ_{it}^{L} also (largely) contains labor market distortions. Figure B.4 shows that the same pattern also holds within individual NACE rev. 1.1 industries.

SAMPLE DISPERSION OF μ_{it}^{M} AND μ_{it}^{L} WITHIN INDUSTRIES

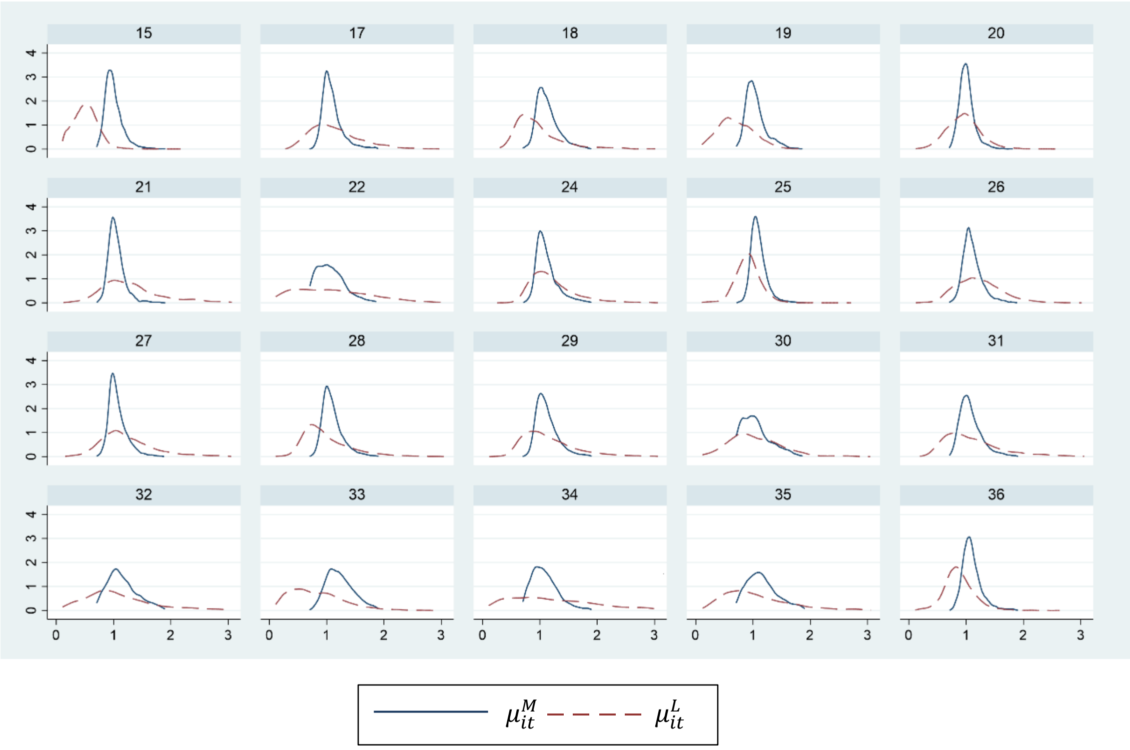

FIGURE B.4 – Kernel density plots for μ_{it}^{M} and μ_{it}^{L} for sample firms in individual two-digit industries. Outliers below and above the 1st and the 99th percentiles are trimmed.

B.4 The impact of output and input price bias

This section tests the importance of controlling for firm-level prices in the estimation of firm-level production functions and labor market power parameters. First, I discuss the effect of ignoring firm-level price variation on the estimated output elasticities. Subsequently, I show the practical importance of controlling for unobserved input and output prices by presenting evidence on non-trivial differences in the estimation of labor market distortions and classification of firms into PD- and ND-regimes.

To start, Table B.2 compares median output elasticities from estimating the production function with and without correcting for unobserved price variation. Columns 1-4 are identical to the main text. Columns 5-8 report output elasticities derived from a production function where firm revenues (left-hand side variable) are deflated with an industry-level deflator (supplied by the statistical office of Germany) and where, simultaneously, the price control function $B_{it}(.)$ and firm wages are omitted from the right-hand side of the production function (3.9). Besides this adjustment, all other variables are still included, i.e. all other control variables in $\boldsymbol{z}_{it}$.

Note that the production function for industry 23 (coke, refined petroleum products, and nuclear fuel) can only be estimated using the comparatively less demanding specification that ignores firm price variation. When not controlling for firm-level prices, median output elasticities for intermediate, labor, and capital inputs across all firms are respectively estimated at 0.71, 0.29 and 0.09, whereas median returns to scale are estimated at 1.10. Compared to the baseline results (columns 1-4), median values for returns to scale and the output elasticity of intermediate inputs are higher, whereas values for the output elasticities of capital and labor are nearly unchanged. The dispersion of the output elasticities of labor and capital as well as the dispersion of returns to scale between industries increases when ignoring output and input price variation, while for intermediate inputs it decreases. Note that when I do not correct for input and output price variation at the firm level, two industries (21 and 33) even display median output elasticities for capital below zero. In total, the number of observations with negative output elasticities dramatically increases when I ignore firm-level price variation. I estimate 17,303 out of 180,384 negative output elasticities in my baseline specification (equals 9.6%) against 33,288 out of 180,749 negative output elasticities when I do not control for output and input price variation (equals 18.4%). As firms with negative output elasticities are inconsistent with the production model I implicitly assume, I drop them. Consequently, ignoring firm-level price variation markedly reduces the amount of observations.

Although controlling for unobserved price variation is indeed helpful when estimating the production function, the impact of this correction is not as strong as shown in De Loecker, Goldberg, Khandelwal, & Pavcnik (2016). The reason is that I simultaneously control or not control for input *and* output price variation at the firm level, whereas De Loecker et al. (2016) show results for the case where they only ignore firm-level input price variation.[54] Still, the importance of controlling for input and output prices at the firm level is evident from my results, which confirms the general notion of the findings in De Loecker et al. (2016).

[54] This is due to the nature of their study. De Loecker et al. (2016) estimate product-level production functions with real quantity on the left-hand side by using only single-product firms in their estimation. Therefore, they do not have to deal with firm-level output prices on the left-hand side of the production function. As discussed in De Loecker & Goldberg (2014), output price and input price biases tend to work against each other, i.e. they partly offset each other.

Table B.2

THE EFFECT OF OUTPUT AND INPUT PRICE BIAS ON MEDIAN OUTPUT ELASTICITIES, BY SECTOR

	Correcting for output and input price variation				Not correcting for output and input price variation			
	Intermediate inputs	Labor	Capital	Returns to scale	Intermediate inputs	Labor	Capital	Returns to scale
Sector	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
15 Food products and beverages	0.63	0.10	0.16	0.89	0.76	0.08	0.30	1.12
17 Textiles	0.67	0.30	0.17	1.14	0.73	0.25	0.18	1.16
18 Apparel, dressing, and dyeing of fur	0.74	0.21	0.15	1.07	0.76	0.28	0.18	1.19
19 Leather and leather products	0.63	0.20	0.03	0.88	0.80	0.20	0.22	1.21
20 Wood and wood products	0.64	0.24	0.08	0.99	0.71	0.26	0.08	1.04
21 Pulp, paper, and paper products	0.70	0.28	0.07	1.02	0.75	0.27	-0.06	0.96
22 Publishing and printing	0.46	0.15	0.38	1.09	0.63	0.29	0.05	0.98
23 Coke, refined petroleum products and nuclear fuel	-	-	-	-	0.74	0.08	0.19	0.95
24 Chemicals and chemical products	0.70	0.25	0.12	1.07	0.77	0.26	0.04	1.07
25 Rubber and plastic products	0.67	0.25	0.07	0.99	0.76	0.24	0.05	1.07
26 Other non-metallic mineral products	0.66	0.32	0.10	1.10	0.72	0.32	0.14	1.22
27 Basic metals	0.68	0.31	0.05	1.02	0.77	0.33	0.02	1.12
28 Fabricated metal products	0.59	0.31	0.12	1.00	0.66	0.33	0.10	1.08
29 Machinery and equipment	0.61	0.37	0.08	1.05	0.68	0.39	0.09	1.15
30 Electrical and optical equipment	0.58	0.32	0.07	0.93	0.79	0.30	0.34	1.48
31 Electrical machinery and apparatus	0.61	0.32	0.10	1.01	0.73	0.32	0.04	1.10
32 Radio, television, and communication	0.66	0.32	0.15	1.09	0.77	0.25	0.10	1.13
33 Medical and precision instruments	0.59	0.27	0.19	1.07	0.67	0.44	-0.01	1.08
34 Motor vehicles and trailers	0.68	0.31	0.26	1.27	0.76	0.20	0.23	1.24
35 Transport equipment	0.64	0.31	0.09	1.09	0.72	0.24	0.01	0.99
36 Furniture manufacturing	0.65	0.28	0.05	0.96	0.74	0.28	0.16	1.19
Across all industries	0.63	0.28	0.10	1.01	0.71	0.29	0.09	1.10

Notes: Table B.2 reports median output elasticities from estimating the production function (3.9) for every NACE rev. 1.1 2-digit industry with sufficient observations, one time with and one time without controlling for unobserved firm-level input and output price variation. Columns 1-4 respectively report the output elasticities for intermediate, labor, and capital inputs as well as the resulting returns to scale when controlling for firm-level input and output prices. Columns 5-8 respectively report the output elasticities for intermediate, labor, and capital inputs as well as the resulting returns to scale when ignoring firm-level input and output price variation. All regressions control for time dummies and are weighted using population weights.

Next, I turn to the labor market imperfection parameter, δ_{it}^{L}, which implies the degree of labor market distortions at the firm level. Table B.3 compares estimates for δ_{it}^{L} for specifications where firm price variation is taken into account and where it is ignored. Columns 1 and 2 are taken from the main text. When comparing columns 1 and 3 one finds that ignoring firm-level price variation increases the median labor market power parameter for nearly every industry. Across all industries, the median of δ_{it}^{L} increases by roughly 56% from about 4,400 to 6,800 euro when I do not correct for unobserved firm price variation. Absolute gaps are comparably less affected from ignoring firm-level prices (columns 2 and 4). However, firms' classification in PD- and ND-firms is determined by δ_{it}^{L}. Thus, when δ_{it}^{L} is overestimated, firms and industries might be wrongly classified into PD-firms.

Table B.4 illustrates this point by presenting two firm classifications. Columns 1-3 refer to a specification where I control for unobserved firm price variation when estimating the production function (this is equivalent to the main text), whereas columns 4-6 present a classification where I ignore firm-level price variation. There are two critical points to note. First, the number of firms I can classify is lower when I do not correct for input and output price variation, which follows from the previous discussion on negative output elasticities. Second, consistent with the existing literature, I indeed classify a higher share of firms as PD-firms when I do not correct for firm-level price variation (61.3% vs. 68.2%). At the industry level this classification bias becomes even worse: Overall, ND-firms dominate seven out of twenty industries when I do correct for firm-level price variation. Ignoring firm-level prices reduces this amount to three out of twenty industries.

Table B.3

THE EFFECT OF OUTPUT AND INPUT PRICE BIAS ON LABOR MARKET DISTORTIONS, BY SECTOR

	Correcting for firm-level price variation		Not correcting for firm-level price variation	
	δ_{it}^{L}	$\lvert\delta_{it}^{L}\rvert$	δ_{it}^{L}	$\lvert\delta_{it}^{L}\rvert$
Sector	(1)	(2)	(3)	(4)
15 Food products and beverages	12,490.55	12,502.39	11,478.53	12,041.93
17 Textiles	11.18	8,851.34	7,825.45	9,248.82
18 Apparel, dressing, and dyeing of fur	4,764.42	8,821.64	1,115.03	8,461.67
19 Leather and leather products	8,864.17	9,793.85	12,599.58	13,386.64
20 Wood and wood products	1,412.29	6,757.43	4,569.01	6,651.92
21 Pulp, paper, and paper products	-6,820.90	12,525.86	6,542.79	9,340.13
22 Publishing and printing	-7,216.08	21,568.79	12,468.62	14,311.95
23 Coke, refined petroleum products and nuclear fuel	-	-	7,936.33	22,506.25
24 Chemicals and chemical products	-1,952.28	11,449.42	-656.52	14,317.75
25 Rubber and plastic products	5,573.45	6,786.98	8,793.55	9,512.16
26 Other non-metallic mineral products	-2,864.04	9,697.13	-3,000.24	10,944.60
27 Basic metals	-3,910.66	12,431.88	-3,112.27	13,820.32
28 Fabricated metal products	5,383.92	11,035.70	6,317.88	10,161.33
29 Machinery and equipment	1,735.73	12,585.09	4,008.70	12,746.07
30 Electrical and optical equipment	-141.15	17,395.99	15,671.15	19,531.86
31 Electrical machinery and apparatus	1,344.55	12,730.50	8,295.99	13,693.74
32 Radio, television, and communication	3,847.69	16,105.19	11,245.22	13,811.32
33 Medical and precision instruments	13,500.65	16,843.87	8,525.01	9,556.00
34 Motor vehicles and trailers	-1,009.48	20,230.48	12,509.43	19,315.73
35 Transport equipment	6,260.02	17,048.74	16,745.34	17,426.00
36 Furniture manufacturing	6,406.75	7,697.29	8,455.05	9,947.98
Total	4,377.00	11,431.60	6,820.24	11,653.46

Table B.3 reports sample median values of labor market distortions for every NACE rev. 1.1 2-digit industry. Columns 1 and 2 report results based on a production function estimation that controls for unobserved firm-level price variation, whereas columns 3 and 4 present results based on a production function that ignores unobserved firm-level price variation. Column 1 and 3 report the median values for the labor market distortion parameter, whereas column 2 and 4 displays median values for the absolute value of the labor market distortion parameter. For both specifications, the top and bottom one percent of observations with respect to the distribution of the labor market distortion parameter are excluded.

Table B.4

THE EFFECT OF OUTPUT AND INPUT PRICE BIAS
ON THE CLASSIFICATION OF FIRMS INTO PD-FIRMS AND ND-FIRMS, BY SECTOR

	Correcting for output and input price variation			Not correcting for output and input price variation		
	Percentage of firm-year observations with $\delta_{it}^{L} > 0$ (PD-firms)	Percentage of firm-year observations with $\delta_{it}^{L} < 0$ (ND-firms)	Number of firm-year observations	Percentage of firm-year observations with $\delta_{it}^{L} > 0$ (PD-firms)	Percentage of firm-year observations with $\delta_{it}^{L} < 0$ (ND-firms)	Number of firm-year observations
Sector	(1)	(2)	(3)	(4)	(5)	(6)
15 Food products and beverages	96.48	3.52	18,520	91.07	8.93	15,588
17 Textiles	50.12	49.88	5,782	80.33	19.67	5,516
18 Apparel, dressing, and dyeing of fur	69.16	30.84	1,767	53.67	46.33	1,869
19 Leather and leather products	80.91	19.09	985	89.58	10.42	1,171
20 Wood and wood products	55.49	44.51	4,759	72.30	27.70	4,354
21 Pulp, paper, and paper products	33.60	66.40	4,217	74.10	25.90	780
22 Publishing and printing	40.06	59.94	1,680	81.59	18.41	4,026
23 Coke, refined petroleum products and nuclear fuel	-	-	-	58.17	41.83	208
24 Chemicals and chemical products	45.44	54.56	11,581	47.64	52.36	9,992
25 Rubber and plastic products	76.49	23.51	11,277	84.04	15.96	8,849
26 Other non-metallic mineral products	42.30	57.70	8,967	42.42	57,58	8,889
27 Basic metals	41.12	58.88	5,954	42.52	57.48	4,960
28 Fabricated metal products	64.86	35.14	23,805	69.49	30.51	23,128
29 Machinery and equipment	53.66	46.34	28,209	58.00	42.00	27,744
30 Electrical and optical equipment	47.52	52.48	909	74.16	25.84	1,277
31 Electrical machinery and apparatus	52.86	47.14	10,260	69.25	30.75	9,049
32 Radio, television, and communication	55.65	44.35	2,681	76.34	23.66	2,532
33 Medical and precision instruments	78.17	21.83	7,764	81.02	18.98	2,608
34 Motor vehicles and trailers	44.39	55.61	6,096	65.90	34.10	5,772
35 Transport equipment	58.31	41.69	2,099	87.65	12.35	1,757
36 Furniture manufacturing	76.88	23.12	5,769	79.46	20.54	7,392
Across all industries	61.32	38.68	163,081	68.17	31,83	147,461

Notes: Table B.4 reports sample percentages for PD-firms and ND-firms for every NACE rev. 1.1 two-digit industry, one time calculated from an estimation of a production function that corrects for firm-level output and input price variation (columns 1-3) and one time calculated from an estimation of a production function that ignores firm-level output and input price variation (columns 4-6). Columns 1 and 4 report the percentage shares of PD-firms and columns 2 and 5 report the percentage shares of ND-firms for both specifications. The number of classifiable firm-year observations is given in columns 3 and 6.

B.5 Trade and the dispersion of labor market power

In analogy to the firm level, four-digit industry-level trade measures are constructed by a revenue weighted aggregation of product-level trade flows to the industry j level.[55] The dispersion of labor market power across firms within four-digit industries is measured by the log of the standard deviation of firms' labor market power parameters across firms classified into the same four-digit industry. I denote this dispersion measure by σ_{jt}^{L}. To investigate how international trade affects the dispersion of labor market power, I run the following regression:

(B.11)
$$\sigma_{jt}^{L} = \gamma_{IMP} IMP_{jt-1}^{CHN} + \gamma_{EXP} EXP_{jt-1}^{CHN} + \upsilon_j + \upsilon_t \ ,$$

where υ_j and υ_t capture industry and time specific effects. When estimating (B.11) by IV, I use the same identification strategy as in the main text and instrument endogenous industry-level trade measures with industry-level imports (exports) flowing from China (instrument group countries) to instrument group countries (China) in total imports (exports) flowing from the world (instrument group countries) to the instrument group countries (world).

Table B.5 shows the associated results from estimating equation (B.11) by OLS (columns 1 and 2) and by IV (columns 3 and 4). In columns 1 and 3 I only control for time fixed effects, whereas in column 2 and 4 I additionally include industry-level fixed effects. When controlling only for time fixed effects, OLS and IV results imply that increasing import competition (export demand) decreases (increases) the dispersion of firms' labor market power within industries (columns 1 and 3). After adding industry fixed effects, the OLS estimates become insignificant. The same holds for the IV estimate of the effect of import competition on σ_{jt}^{L}. However, the IV specification also reveals that there indeed exists a

[55] This weights trade flows with their importance for domestic firms within the respective industries.

positive causal relationship between Chinese export demand and the industry-level dispersion of firms' labor market power (column 4). This implies that increasing foreign demand contributes to an increase in labor market power inequality across firms, and, therefore, also across workers employed in different firms, within industries. As shown in the main text, this finding can be rationalized by heterogeneous responses of firms with and without labor market power to an increase in foreign demand.

Table B.5

DISPERSION OF LABOR MARKET POWER AND TRADE

	OLS		IV	
	σ_{jt}^{L}	σ_{jt}^{L}	σ_{jt}^{L}	σ_{jt}^{L}
	(1)	(2)	(3)	(4)
IMP_{jt-1}^{CHN}	-0.0167***	0.00097	-0.0246***	0.00085
	(0.00458)	(0.00505)	(0.00638)	(0.00727)
EXP_{jt-1}^{CHN}	0.0576***	0.00901	0.108***	0.116***
	(0.0172)	(0.00839)	(0.0336)	(0.0390)
Time FE	YES	YES	YES	YES
Industry FE	NO	YES	NO	YES
Observations	2,730	2,728	2,730	2,728
R-squared	0.060	0.739	0.033	0.724
First-stage F-test	-	-	10.65	17.16
Number of Industries	231	229	231	229

Notes: Table B.5 reports results from estimating equation (B.11) by OLS and IV. OLS-results are reported in columns 1 and 2. IV-results are reported in columns 3 and 4. The dependent variable in all columns is the log of the industry-level standard deviation of the firm-specific labor market distortions parameter. Specifications reported in column 1 and 3 include only time fixed effects, while specifications in columns 2 and 4 additionally control for four-digit industry fixed effects. Significance: *10 percent, **5 percent, ***1 percent.

B.6 Using trade measures based on the BRICS country group and excluding firms that switched their type

Table B.6

LABOR MARKET DISTORTIONS AND TRADE, THE BRICS COUNTRY GROUP

	All Firms		PD-firms		ND-firms	
	δ_{it}^{L}	$\lvert\delta_{it}^{L}\rvert$	δ_{it}^{L}	$\lvert\delta_{it}^{L}\rvert$	δ_{it}^{L}	$\lvert\delta_{it}^{L}\rvert$
	(1)	(2)	(3)	(4)	(5)	(6)
IMP_{it-1}^{BRICS}	228.10***	-54.69	124.60***	88.96**	229.40*	-207.40**
	(59.50)	(42.64)	(45.32)	(39.10)	(117.80)	(104.40)
EXP_{it-1}^{BRICS}	-261.70***	180.90***	-27.36	21.82	-385.20**	389.60***
	(72.00)	(58.16)	(68.03)	(56.82)	(152.40)	(128.60)
Firm ∗ Industry FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
Firm level controls	YES	YES	YES	YES	YES	YES
Observations	108,902	108,902	63,240	63,240	41,323	41,323
R-squared	0.920	0.864	0.832	0.845	0.877	0.888
First-stage F-test	179.40	179.40	57.43	57.43	53.09	53.09
Number of firms	24,330	24,330	16,485	16,485	8,745	8,745

Notes: Table B.6 reports results from estimating equation (3.12) by IV using trade measures based on trade flows between Germany and the BRICS country group. Columns 1 and 2 report results for the full sample of firms. Columns 3 and 4 report results for $t-1$ PD-firms, whereas columns 5 and 6 report results for $t-1$ ND-firms. In columns 1, 3, and 5 the dependent variable is the labor market distortion parameter, δ_{it}^{L}, whereas in columns 2, 4, and 6 it is the absolute value of the labor market distortion parameter, $|\delta_{it}^{L}|$. All regressions include time and industry times firm fixed effects and controls for firm size, firms' worker outsourcing rate, firms' share of researchers in the entire workforce, firms' market share and firms' labor productivity. Regressions are weighted using population weights. Standard errors are clustered at the firm level. The top and bottom one percent of observations with respect to the distribution of the labor market distortion parameter are excluded. Significance: *10 percent, **5 percent, ***1 percent.

This section shows that all results for the effects of trade on labor market distortions reported in the main text are robust to i) using trade measures based on trade flows between Germany and the BRICS country group (Brazil, Russia, India, China, and South Africa) and to ii) excluding firms which changed their classification into PD- and ND-firms between the periods t and $t-1$.[56]

[56] OLS and IV results for both robustness checks follow a scheme, similar to the one of the main text (results are available on request).

Table B.7

LABOR MARKET DISTORTIONS AND TRADE, EXCLUDING FIRMS THAT SWITCHED THEIR TYPE				
	PD-firms		ND-firms	
	δ_{it}^{L}	$\lvert\delta_{it}^{L}\rvert$	δ_{it}^{L}	$\lvert\delta_{it}^{L}\rvert$
	(3)	(4)	(5)	(6)
IMP_{it-1}^{BRICS}	117.60***	117.60***	202.00	-202.00
	(42.99)	(42.99)	(123.80)	(123.80)
EXP_{it-1}^{BRICS}	49.94	46.94	-656.40***	656.40***
	(102.9)	(102.9)	(218.50)	(218.50)
Firm $*$ Industry FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Firm level controls	YES	YES	YES	YES
Observations	59,426	59,426	37,826	37,826
R-squared	0.847	0.847	0.890	0.890
First-stage F-test	83.73	83.73	26.32	26.32
Number of firms	15,615	15,615	7,819	7,819

Notes: Table B.7 reports results from estimating equation (3.12) by IV separately for PD- and ND-firms. Columns 1 and 2 report results for PD-firms, whereas columns 3 and 4 report results for ND-firms. In columns 1 and 3 the dependent variable is the labor market distortion parameter, δ_{it}^{L}, whereas in columns 2 and 4 it is the absolute value of the labor market distortion parameter, $|\delta_{it}^{L}|$. All regressions include time and industry times firm fixed effects and controls for firm size, firms' worker outsourcing rate, firms' share of researchers in the entire workforce, firms' market share and firms' labor productivity. Regressions are weighted using population weights. Standard errors are clustered at the firm level. The top and bottom one percent of observations with respect to the distribution of the labor market distortion parameter are excluded. Firms which changed their classification into PD- and ND-firms between period t and $t-1$ are excluded. Significance: *10 percent, **5 percent, ***1 percent.

Table B.6 shows the results corresponding to the robustness check which uses the BRICS country group as Germany's trade partner. Table B.6 first pools all firms (columns 1 and 2) and subsequently separates them into $t-1$ PD-firms (columns 3 and 4) and ND-firms (columns 5 and 6).

After comparing Table B.6 with Tables 3.5 and 3.6 from the main text, one sees that, throughout the complete set of results, changing the trade partner from China to the BRICS country group leaves my findings qualitatively unchanged.

Table B.7 shows the results corresponding to the second robustness check which runs the regressions for PD and ND-firms again after excluding firms which changed their classification into PD- and ND-firms between the periods t and $t-1$. Table B.7 first reports results for PD-firms (columns 1 and 2) and subsequently shows results for ND-firms (columns 3 and 4).

As consequence of eliminating firms which switched their type, results for δ_{it}^{L} and $|\delta_{it}^{L}|$ are identical. Again, comparing Table B.7 with Table 3.6 of the main text shows that my results are qualitatively unchanged when excluding firms that switched their classification into PD- and ND-firms.

B.7 First stage regression results for main IV-results

Tables B.8, B.9, and B.10 report the first stage regression results for the main IV-specifications using the baseline measure of labor market distortions, which is derived form a production estimation framework controlling for firm-specific price variation. The first stage regressions in Tables B.8, B.9, and B.10 respectively refer to the reported IV-results in Tables 3.5, 3.6, and 3.7 of the main text. I denote the firm-level instrument variables for my measures of import competition and export demand respectively by IMS_{it}^{INS} and EXS_{it}^{INS}.

Table B.8

FIRST STAGE REGRESSION RESULTS
FOR TABLE 3.5 OF THE MAIN TEXT

	IMP_{it-1}^{CHN} (1)	EXP_{it-1}^{CHN} (2)	IMP_{it-1}^{CHN} (3)	EXP_{it-1}^{CHN} (4)
IMS_{it-1}^{INS}	0.263***	0.0188***	0.263***	0.0188***
	(0.0175)	(0.00269)	(0.0175)	(0.00269)
EXS_{it-1}^{INS}	-0.0463***	0.165***	-0.0462***	0.166***
	(0.00887)	(0.0116)	(0.00888)	(0.0116)
μ_{it}^{M}	-	-	0.0675	0.104*
			(0.0702)	(0.0615)
Firm x Industry FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Observations	108,904	108,904	108,904	108,904
R-squared	0.946	0.825	0.946	0.825
Number of firms	24,334	24,334	24,334	24,334

Notes: Table B.8 reports results from the first stage regressions when estimating equation (3.12) by IV using the full sample of firms. The dependent variable in columns 1 and 3 is the lagged import competition measure, while in columns 2 and 4 it is the lagged export opportunity measure. All regressions include time and industry times firm fixed effects and controls for firms' size, worker outsourcing rate, share of researchers in the entire workforce, market share, and labor productivity. All regressions are weighted using population weights. Standard errors are clustered at the firm level. The top and bottom one percent of observations with respect to the distribution of the labor market distortion parameter are excluded. Significance: *10 percent, **5 percent, ***1 percent.

Table B.9

FIRST STAGE REGRESSION RESULTS
FOR TABLE 3.6 OF THE MAIN TEXT

Panel A: PD-firms	IMP_{it-1}^{CHN} (1)	EXP_{it-1}^{CHN} (2)	IMP_{it-1}^{CHN} (3)	EXP_{it-1}^{CHN} (4)
IMS_{it-1}^{INS}	0.266***	0.0199***	0.266***	0.0199***
	(0.0164)	(0.00387)	(0.0164)	(0.00387)
EXS_{it-1}^{INS}	-0.0533***	0.161***	-0.0533***	0.161***
	(0.00985)	(0.0139)	(0.00985)	(0.0139)
μ_{it}^{M}	-	-	0.0940	-0.00820
			(0.0703)	(0.0658)
Firm x Industry FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Firm-level controls	YES	YES	YES	YES
Observations	63,271	63,271	63,271	63,271
R-squared	0.952	0.832	0.952	0.832
Number of firms	16,493	16,493	16,493	16,493

Panel B: ND-firms	IMP_{it-1}^{CHN} (1)	EXP_{it-1}^{CHN} (2)	IMP_{it-1}^{CHN} (3)	EXP_{it-1}^{CHN} (4)
IMS_{it-1}^{INS}	0.228***	0.0175***	0.228***	0.0174***
	(0.0230)	(0.00397)	(0.0231)	(0.00398)
EXS_{it-1}^{INS}	-0.0445***	0.159***	-0.0445***	0.159***
	(0.00915)	(0.0199)	(0.00915)	(0.0199)
μ_{it}^{M}	-	-	-0.0726	0.335**
			(0.204)	(0.171)
Firm x Industry FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Firm-level controls	YES	YES	YES	YES
Observations	41,301	41,301	41,301	41,301
R-squared	0.955	0.871	0.955	0.871
Number of firms	8,736	8,736	8,736	8,736

Notes: Table B.9 reports results from the first stage regressions when estimating equation (3.12) by IV using separate samples for PD-firms (Panel A) and ND-firms (Panel B). The dependent variable in columns 1 and 3 is the lagged import competition measure, while in columns 2 and 4 it is the lagged export opportunity measure. All regressions include time and industry times firm fixed effects and controls for firms' size, worker outsourcing rate, share of researchers in the entire workforce, market share, and labor productivity. All regressions are weighted using population weights. Standard errors are clustered at the firm level. The top and bottom one percent of observations with respect to the distribution of the labor market distortion parameter are excluded. Significance: *10 percent, **5 percent, ***1 percent.

Table B.10

FIRST STAGE REGRESSION RESULTS
FOR TABLE 3.7 OF THE MAIN TEXT

	PD-firms		ND-firms	
	IMP_{it-1}^{CHN} (1)	EXP_{it-1}^{CHN} (2)	IMP_{it-1}^{CHN} (3)	EXP_{it-1}^{CHN} (4)
IMS_{it-1}^{INS}	0.269***	0.0200***	0.229***	0.0174***
	(0.0167)	(0.00388)	(0.0230)	(0.00397)
EXS_{it-1}^{INS}	-0.0521***	0.161***	-0.0453***	0.159***
	(0.00985)	(0.0139)	(0.00916)	(0.0199)
Firm x Industry FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Firm-level controls	YES	YES	YES	YES
Observations	63,271	63,271	41,301	41,391
R-squared	0.951	0.832	0.955	0.871
Number of firms	16,493	16,493	8,736	8,733

Notes: Table B.10 reports results from the first stage regressions when estimating equation (3.12) without any control variables by IV using separate samples for PD-firms and ND-firms. Columns 1 and 2 report results for PD-firms. Columns 3 and 4 report results for ND-firms. The dependent variable in columns 1 and 3 is the lagged import competition measure, while in columns 2 and 4 it is the lagged export opportunity measure. All regressions include time and industry times firm fixed and are weighted using population weights. Standard errors are clustered at the firm level. The top and bottom one percent of observations with respect to the distribution of the labor market distortion parameter are excluded. Significance: *10 percent, **5 percent, ***1 percent.

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Chapter 4

Micro-Mechanisms behind Declining Labor Shares: Market Power, Production Processes, and Global Competition

4.1 Introduction

THE ECONOMIC VALUATION OF WORK, reflected in the wage share in economic output, is declining. This not only has severe distributional consequences; but it 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 large body of literature debates the causes and mechanisms behind the global decline of wage shares.[57] Yet, the sources and implications of this decline are still not well understood, making predictions on its future course difficult and limiting our abilities to design appropriate policies in light of this secular trend.

This article contributes to this understanding by developing a parsimonious micro-founded production side theory offering three competing explanations for the fall of the labor share: an increase in firms' product market power, an increase in firms' labor market power, or a fall in firms' output elasticity of labor, which reflects a decreasing importance of labor in firms' production activities. The former two explanations both refer to an increase in market distortions, which, due to the associated reduction in aggregate output, can be viewed as an

[57] E.g. Blanchard & Giavazzi (2003); Elsby, Hobijn, & Şahin (2013); Karabarbounis & Neiman (2013, 2014); Lawrence (2015); Acemoglu, & Restrepo (2016); Barkai (2016); Koh, Santaeulàlia-Llopis, & Zheng (2016); Autor, Dorn, Katz, Patterson, & Van Reenen (2017); Caballero, Farhi, & Gourinchas (2017); De Loecker & Eeckhout (2018); Karabarbounis & Neiman (2018); Kehrig & Vincent (2018).

inefficient scenario. 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 naturally results from an (aggregate) output maximizing (re)allocation of factor shares.

By applying my framework to 20 years of micro-data on German manufacturing sector firms, I provide three novel contributions to the literature. First, I use my theory to quantify the relative contribution of market distortions (inefficient scenario) and transforming production processes (efficient scenario) to a fall of the labor share. This assessment addresses recent and influential work suggesting that falling labor shares might be caused by increasing product market power (e.g. Barkai (2016); De Loecker & Eeckhout (2018); De Loecker, Eeckhout, & Unger (2018)). As result of this recent work, the literature is now confronted with the question about the extent to which market distortions indeed drive the decline of labor shares. Within my framework, I can answer this question by a simple thought experiment: If declining firm-level labor shares result from efficient changes in production processes, output elasticities of labor will decrease in concordance with labor shares. If labor shares, however, fall due to an increase in firms' product or labor market power, one will observe a wedge between the aggregate labor share and the aggregate output elasticity of labor. Applying this idea to the German manufacturing sector, I find that 70% of the decline in its labor share between 1995 and 2014 are explained by a decrease in the output elasticity of labor. The remaining 30% are accounted for by firms' increasing labor and product market power. Although constituting the minor share, I argue that this increase in market distortions implies room for policies that simultaneously increase economic output and labor's share of it. I discuss specific suggestions for such policies for Germany's manufacturing sector, given its observed joint distribution of market power and firm size.

Second, by separately analyzing product and labor market power, I contribute to the recent literature on rising firm market power also from a methodological point of view. Existing studies usually assume competitive labor markets (e.g. Barkai (2016); Autor et al. (2017); De Loecker & Eeckhout (2018); De Loecker et al. (2018)). This attributes variation in labor shares that does not result from changing output elasticities of labor (which are often assumed to be constant) by design to variation in product market power. Furthermore, assuming competitive labor markets makes it unclear whether the "rise of market power" documented in the literature reflects a rise in firms' product or labor market power. Clarifying this is, however, important as policies targeting output market power are different from those targeting labor market power (e.g. trade liberalization or minimum wages affect both types of market power differently). For Germany's manufacturing sector I document a high level of aggregate firm labor market power, whereas product markets are relatively competitive. Hence, monopsonistic labor markets are a more relevant source of firm market power in Germany's manufacturing sector than monopolistic product markets. This echoes recent academic work suggesting that welfare losses from labor market power might even be larger than those from product market power (Naidu, Posner, & Weyl (2018); Marinescu & Hovenkamp (2018)). Over time, however, both types of market power increase.

Third, I use my framework to assess the role of global competition for driving changes in firm-level labor shares, product market power, labor market power, and output elasticities of labor. This sheds new light on the channels through which trade affects labor shares and contributes to an ongoing debate on the extent to which globalization accounts for secular changes in labor shares.[58] Notably, I use detailed information on firms' nine-digit product mix to construct firm-specific measures of final product import competition and export market

[58] E.g. Rodrik (1997); Harrison (2005); Elsby et al. (2013); Karabarbounis & Neiman (2014); Autor et al. (2017); Doan & Wan (2017); Gupta & Helble (2018).

demand, which account for firms being active in multiple industries. For causal identification, I use an instrumental variable strategy, similar to Autor, Dorn, & Hanson (2013) and Dauth, Südekum, & Findeisen (2014, 2018). My main results document a significant role for foreign demand in explaining falling labor shares by increasing labor market power within firms and by reallocating economic activity towards large exporting firms characterized by smaller labor shares than non-exporting firms. In contrast, import competition increases labor shares and reduces labor market power within firms. Notably, I cannot validate that increasing import competition or export demand leads to a restructuring of firms' production that decreases the importance of labor within firms. Instead, other factors seem to drive the observed fall in the output elasticity of labor.

The data to apply my framework is based on an administrative yearly firm-product-level panel on Germany's manufacturing sector for the period 1995-2014. This dataset is particularly suitable for my study as it contains information on firms' product quantities and prices. From that I can capture *firm-specific* price variation, which is crucial for a framework that investigates *firm-specific* market power. In most studies, such information is not accessible.

By providing a micro-econometric framework to analyze the mechanism behind declining labor shares I complement a large existing macroeconomic literature from which Dixon & Lim (2018) is closest to this paper.[59] Those authors derive a model similar to the framework of this article but within a macro-data setting. The advantage of using micro-data is that I can abstain from an extensive set of assumptions on demand and production technology, necessary within a macro-model. In particular, my approach nests most common models of demand, like CES and VES frameworks, and different models of competition (e.g.

[59] See Schneider (2011) and Giovannoni (2014a, 2014b) for a comprehensive review.

monopolistic and Bertrand competition). Besides that, I can loosen typically employed assumptions on competitive labor markets without imposing a priori restrictions on the price setting of factor markets (e.g. whether labor markets are characterized by monopsonistic or efficient bargaining regimes). A particular convenient aspect of using micro-data is that it allows for a simple and unrestrictive way in which I can introduce time variation in firm-level market power parameters and output elasticities. I understand this to be the reason I uncover a stark increase in aggregate firm labor market power and a strong fall in the aggregate output elasticity of labor, which are both undocumented in the literature. The severe implication of the latter is that common production models assuming constant output elasticities, as most applied Cobb-Douglas specifications, are rejected by the data.

In addition to the mentioned literature, this study ties into the long run debate on the movement of 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 the 1950s Solow (1958) published a "skeptical note" on the presumed constancy of factor shares. In earlier work Keynes (1939) called the factor share stability "a bit of a miracle". Since the observation of a declining global labor share starting in the 1980s, this strand of literature benefits from a renewed research interest. Today, the most prominent arguments explaining falling labor shares feature a vital role for biased technological change or globalization, which facilitates the offshoring of domestic production activities (e.g. Acemoglu (2003); Harrison (2005); Elsby et al. (2013); Karabarbounis & Neiman (2014); Caballero et al. (2017)). Other work highlights the erosion of labor market institutions (e.g. Blanchard & Giavazzi (2003)) and discusses the importance of measurement error in explaining declining labor shares (e.g. Koh et al. (2016)). Most recently, the literature discusses how rising product market power and firm concentration might have contributed to falling labor shares (Autor et al. (2017); De Loecker & Eeckhout (2018); De Loecker et al. (2018)).

I view my study as nesting most of those potential driving forces into a simple framework, in which changes in the economic environment affect labor shares through changes in i) production processes, ii) labor market power, and iii) product market power. My framework fits the data extremely well. While being parsimonious, it accounts for 94% of cross-sectional firm-level variation in labor shares. Thus, it captures nearly the entire change in the labor share in my data.

The remainder proceeds as follows: Section 4.2 describes the data. Section 4.3 derives the framework from which I infer on the mechanisms behind declining labor shares. Here I also discuss the estimation routine used to calculate time varying output elasticities. Section 4.4 shows descriptive evidence for the variables of interest, conducts decomposition exercises, and calculates the contribution of efficient and inefficient sources to the decline of the labor share. Section 4.5 investigates the casual relationship between final product trade and declining labor shares. Section 4.6 concludes.

4.2 Data

I use yearly panel data on German manufacturing sector firms with more than 20 employees from the cost structure survey, the investment survey, and the AFiD-database covering a period of two decades from 1995 to 2014. All datasets are supplied by the statistical offices of Germany.[60] As firms are obliged to report by law, the data are of

[60] Data source: Research Data Centre of the Federal Statistical Office of Germany and the Statistical Offices of the German Länder. Names of statistics used: *"AFiD-Modul Produkte", "AFiD-Panel Industriebetriebe", "AFiD-Panel Industrieunternehmen", "Investitionserhebung im Bereich Verarbeitendes Gewerbe, Bergbau und Gewinnung von Steinen und Erden", "Panel der Kostenstrukturerhebung im Bereich Verarbeitendes Gewerbe, Bergbau und Gewinnung von Steinen und Erden".*

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, however, variables from the cost structure survey are only collected for a representative and periodically rotating subsample covering roughly 40% of all manufacturing firms with more than 20 employees. This includes information on intermediate input expenditures or labor costs by various categories.[61]

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, having a time consistent industry classification at the firm level is vital to my study. Moreover, the procedure to recover output elasticities and market power parameters heavily relies on time consistent industry codes. Recovering such an industry classification from official concordance tables is, however, problematic as they contain a large amount of ambiguous sector reclassifications.

To circumvent 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.[62] 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. However, reclassifying products is 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

[61] I drop firms with negative value-added and outliers with respect to value-added and revenue growth, value-added over revenue, and deflated sales over production inputs and wages. I also purge the product data (which is separately given) from outliers in terms of price growth and price deviations from the average product price.

[62] I am thankful to Richard Bräuer with whom I developed this classification cross-walk.

products (I observe what firms produce before and after breaks in classifications). Having constructed the product-industry classification, I attribute every firm to the industry in which it generates most of its revenue. In fact, the statistical offices of Germany use a similar approach to classify firms into industries.[63] When comparing my classification with the one of the statistical offices for the years 2002-2008 (years in which industries are already reported in NACE rev 1.1), I find that the custom two-digit and four-digit classification of firms into industries respectively matches the classification of the statistical offices in 95% and 86% of all cases.

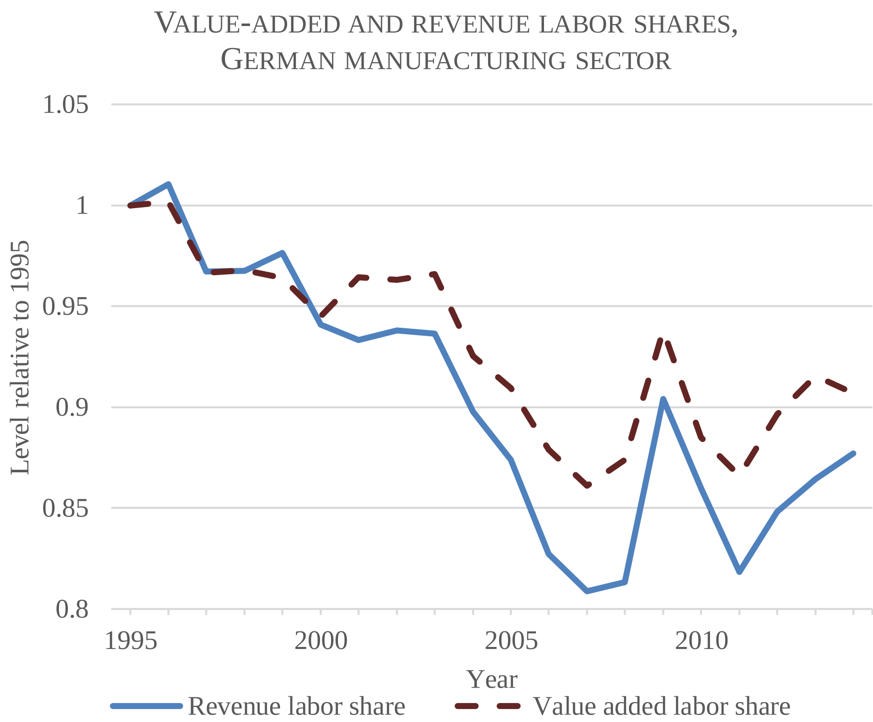

FIGURE 4.1 – Value-added and revenue labor shares for the German manufacturing sector. Sample firms.

Using the available 20 years of data, Figure 1 shows how aggregate manufacturing sector wage shares in value-added and revenue evolve over the observation period in Germany. The depicted fall in wage shares is impressive. Over those two decades, revenue (value-added)

[63] Roughly speaking, the statistical offices classify firms into industries based on their distribution of revenue, employment, and value-added across industries.

wage shares decline by 12 (9) percent. This corresponds to an absolute decline of the revenue (valued-added) labor share from 0.268 (0.759) to 0.235 (0.688).

Note the large spike during the crisis in 2009. Intuitively, this phenomenon can be explained by sticky wage and labor quantity adjustments (i.e. labor hoarding) in response to negative output shocks. Qualitatively, the decline in value-added and revenue wage shares is similar, with the latter being percentage wise stronger. This indicates a shortening of firms' value chain as one can transform revenue labor shares into value-added labor shares by multiplying them with the revenue over value-added ratio. However, we will focus on potential causes at a later point. Beforehand, the next section derives a simple theory fixing ideas on how labor shares are linked to market power and the importance of labor in firms' production processes.

4.3 A production side theory of the labor share

This section derives a parsimonious theory that connects firm-level labor shares to output elasticities of labor and firms' market power in product and labor markets. Section 4.3.1 describes the derivation of this framework and discusses its underlying assumptions. The approach I apply here is similar to Dobbelaere & Mairesse (2013) and De Loecker et al. (2018). Section 4.3.2 presents the empirical strategy to recover necessary parameters.

4.3.1 Theoretical framework

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

$$Q_{it} = Q_{it}(.) = Q_{it}(L_{it}, K_{it}, M_{it}, e^{\omega_{it}}) , \tag{4.1}$$

where Q_{it} represents total physical output and L_{it}, K_{it}, and M_{it} denote labor, capital, and intermediate inputs used in the production of Q_{it}. Firm-specific total factor productivity is denoted by ω_{it}. 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 (more details on factor markets are discussed below).[64] The only restriction on the functional form of (4.1) that I impose is that it is continuous and twice differentiable.

Equation (4.1) describes a physical production process. A production model like (4.1) that transforms physical inputs into physical outputs approximates firms' underlying production technology more closely than a value-added specification. This is because the value-added concept has no morphological correlate, i.e. there is no market for value-added.[65]

Firms demand labor and capital inputs on imperfectly competitive factor markets. Consequently, those factor markets feature a certain degree of market power, either held by firms or suppliers of labor and capital. With respect to intermediate inputs, I follow the literature covering the estimation of markups and production functions and assume that intermediate input markets are flexible and competitive.[66] For the rest of this article I focus on labor markets because market power on labor markets will be of key interest when exploring potential mechanisms behind declining labor shares.

As shown by a large labor market literature, imperfections in labor markets that give firms or employees labor market power translate into wedges between marginal revenue products of labor and wages:

[64] This is consistent with labor and capital inputs both facing adjustment frictions but labor being more flexible than capital. The assumption of quasi-fixed labor inputs is employed in several studies (e.g. in Ackerberg & Hahn (2015) for Chile, in De Loecker et al. (2016) for India, and in Valmari (2016) for Finland). Given the high degree of employment protection in Germany (OECD (2018)), it is justified to the treat labor as a quasi-fixed input in my case.

[65] In fact, Bruno (1978) showed that it demands restrictive assumptions to motivate the existence of a value-added production function. For a discussion on the different production concepts, I refer to Bruno (1978), Diewert (1978), Baily (1986), and Gandhi, Navarro, & Rivers (2017b).

[66] E.g. Levinsohn & Petrin (2003); Petrin & Levinsohn (2012); Petrin & Sivadasan (2013); Dobbelaere & Mairesse (2013); Ackerberg, Caves, & Fazer (2015); Lu & Yu (2015); De Loecker et al. (2016); Gandhi, Navarro, & Rivers (2017a); Dobbelaere & Kiyota (2018); De Loecker et al. (2018).

(4.2) $$(1 + \tau_{it}^{L}) = \frac{w_{it}}{MRPL_{it}},$$

where w_{it} and $MRPL_{it}$ denote the wage and the marginal revenue product of labor.[67] $\tau_{it}^{L} > -1$ symbolizes the wedge between both variables. The existence of such a wedge can be interpreted as a signal of labor market power in the broader sense as it reflects an inefficient distortion of rents towards the firm ($\tau_{it}^{L} < 0$) or its employees ($\tau_{it}^{L} > 0$).

With respect to the specific frictions that drive τ_{it}^{L}, I stay agnostic. In particular, I do not invoke assumptions on market structure or the exogeneity of wages to restrict τ_{it}^{L} to a specific kind of distortion because such assumption would not change the mathematical nature of τ_{it}^{L} in the data. A key point to note, however, is that there are typically some underlying adjustment frictions on labor markets that create labor market power (e.g. Manning (2003); Naidu et al. (2018)).

For instance, in situations where $\tau_{it}^{L} < 0$, firms could have wage setting power emerging from worker-specific moving costs or local preferences driving wages below competitive levels. This is typically observed on monopsonistic labor markets. In contrast, reasons for observing labor market power on the employees' side ($\tau_{it}^{L} > 0$) could be the presence of strong trade unions or inefficiently working employees that cannot be dismissed due to hiring and firing costs (e.g. McDonald & Solow (1981); Rebitzer & Taylor (1991); Dobbelaere & Mairesse (2013)). In the framework described here, state interventions like effective minimum wages or a strengthening of employment protection laws raise τ_{it}^{L}. To provide more intuition, I present two formally derived examples on how labor market imperfections translate into market power in labor markets in Appendix C.1.

[67] See for instance Dobbelaere & Mairesse (2013) and the literature cited therein.

I now derive a formula describing how labor shares connect to output elasticities of labor and market power in product and labor markets. I start by following De Loecker & Warzynski (2012), who have shown that one can formulate an expression for the firm's product market power from its optimization problem by using a first order condition with respect to a flexible input that is bought on a competitive market. In my case, this refers only to the intermediate input. As shown in Appendix C.2, the associated output market power parameter, μ_{it}, is given by:

$$\mu_{it} = \theta_{it}^{M} * \frac{P_{it}Q_{it}}{z_{it}M_{it}}, \quad (4.3)$$

where P_{it} and z_{it} denote the firm's output price and unit costs for intermediate inputs. θ_{it}^{X} denotes the output elasticity of input $X = \{L, M, K\}$. $\mu_{it} > 1$ indicates that the firm possesses product market power. From reformulating equation (4.2), one receives a similar expression linking product to labor market power:

$$\mu_{it} = \theta_{it}^{L} * \frac{P_{it}Q_{it}}{w_{it}L_{it}}(1 + \tau_{it}^{L}). \quad (4.4)$$

Combining (4.3) and (4.4) gives:

$$\gamma_{it} \equiv \frac{1}{(1 + \tau_{it}^{L})} = \frac{\theta_{it}^{L}}{\theta_{it}^{M}} * \frac{z_{it}M_{it}}{w_{it}L_{it}}, \quad (4.5)$$

where γ_{it} defines a measure of firms' labor market power and $\gamma_{it} > 1$ signals positive labor market power for the firm.[68]

[68] For the derivation see Appendix C.2. In a similar way, Dobbelaere & Kiyota (2018) define a parameter of firm-level labor market imperfections (i.e. labor market power) as: $\gamma_{it} = \theta_{it}^{L} \frac{P_{it}Q_{it}}{w_{it}L_{it}} - \theta_{it}^{M} \frac{P_{it}Q_{it}}{z_{it}M_{it}}$.

Finally, combining (4.4) with (4.5) gives an expression describing the firm-level wage share in revenue as a function of firm-specific output market power, labor market power, and the output elasticity of labor:

(4.6) $$LS_{it} \equiv \frac{w_{it}L_{it}}{P_{it}Q_{it}} = \frac{\theta_{it}^{L}}{\mu_{it}\gamma_{it}}.$$

Equation (4.6) implies that a fall in the firm-level wage share in sales can be a result of increasing product market power (μ_{it}), increasing labor market power (γ_{it}), or a decreasing output elasticity of labor (θ_{it}^{L}), which, in the broadest sense, reflects the importance of labor in the firm's production activities.

While being parsimonious, the right-hand side of equation (4.6) captures a variety of different economic aspects. Preference structures and product demand factors are nested in μ_{it}, which can also be expressed as a function of the product price elasticity of demand (De Loecker & Scott (2016)). Simultaneously, γ_{it} captures labor market imperfections and describes the interplay between labor supply and demand side, while θ_{it}^{L} reflects technological aspects leading to factor substitution. Hence, although not explicitly modelled, equation (4.6) captures a broad set of different economic forces. This, however, also implies that θ_{it}^{L}, γ_{it}, and μ_{it} are not fundamental or necessary exogenous model parameters. They instead reflect channels through which changes in the economic environment and changes in firms' behavior (e.g. technology adoption) impact on the labor share.

Dividing (4.6) by the ratio of nominal value-added to sales, $\frac{VA_{it}}{P_{it}Q_{it}} \equiv \kappa_{it}$, gives an expression for the value-added labor share:

(4.7) $$LS_{it}^{VA} \equiv \frac{w_{it}L_{it}}{VA_{it}} = \frac{\theta_{it}^{L}}{\mu_{it}\gamma_{it}\kappa_{it}}.$$

This shows how changes in firms' value-added depth explain the wedge between the time trends of LS_{it}^{VA} and LS_{it} displayed in Figure 4.1.

For the subsequent paper, I focus on the gross output labor share, as it results more naturally from the firm-level production perspective and lends itself to a more reasonable aggregation and decomposition of wage shares and market power parameters (see below). If I would instead apply a value-added concept, I would down-weight intermediate input intensive firms. This is something I explicitly want to avoid because there might be interesting relationships between the intensity of intermediate inputs used in firms' production activities and i) the importance of labor to firms or ii) firms' labor market power, which I want to capture.[69]

Many recent studies use a similar framework to motivate that rising *output* market power could have a significant role in explaining falling labor shares (e.g. Barkai (2016); Autor et al. (2017); De Loecker & Eeckhout (2018)). The key difference between existing work and the framework used here is that, in addition to product market power, I allow for time varying output elasticities and imperfect functioning labor markets to affect labor shares.

In absence of any output or input market power, revenue wage shares equal the corresponding output elasticities of labor. I term changes in the labor share that correspond to changes in the output elasticity of labor 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 the labor share as inefficient when it results from an increase in output or input market power as rising market power on factor and products markets lowers aggregate output. The latter is simply because firms with market power in

[69] Using the gross output concept also follows De Loecker & Eeckhout (2018) and De Loecker et al. (2018).

factor or product markets demand too little production inputs and produce too little output (De Loecker et al. (2018); Mertens (2018); Van Reenen (2018)).

To shed light on whether declining labor shares are an efficient (decrease in θ_{it}^L) or an inefficient (increase in μ_{it} or γ_{it}) outcome, I use a gap methodology. The associated measure of inefficiency is:

$$\psi_{it} \equiv LS_{it} - \theta_{it}^L \,. \tag{4.8}$$

The intuition behind equation (4.8) is simple. Every deviation from $\psi_{it} = 0$ indicates that labor shares are higher or smaller than under counterfactually competitive output and input markets ($\mu_{it} = \gamma_{it} = 1$). From an efficiency perspective, both, negative and positive gaps are a signal of distortions. When the decline of wage shares is caused by a rise of firms' output or input market power, ψ_{it} declines over time. If this is not the case, then the above framework implies, that declining labor shares are an efficient outcome (i.e. associated with changing production processes).

4.3.2 Recovering the output elasticity of labor

Before evaluating (4.6) empirically, one first needs to recover θ_{it}^L from estimating a production function. Depending on the functional form of the production function, θ_{it}^L varies between firms and across time. Using a traditional Cobb-Douglas specification would lead to *time constant* and *industry-specific* output elasticities. Hence, under a Cobb-Douglas production technology, the entire decline in the labor share is, by definition, attributed to rising output or labor market power. To avoid this, I apply a translog production model, which allows for time- and firm-specific output elasticities:

$$q_{it} = \boldsymbol{\phi}_{it}'\boldsymbol{\beta} + \omega_{it} + \varepsilon_{it} \,, \tag{4.9}$$

where lower-case letters denote logs. $\boldsymbol{\phi}_{it}$ 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.[70]

Before estimating output elasticities from (4.9), I first need to calculate q_{it}, which is not directly observable for multi-product firms. To circumvent this problem, I closely follow Eslava, Haltiwanger, Kugler, & Kugler (2004) in their calculation of a firm-specific price index, π_{it}. I use this price index to purge firm revenues (of all firms) from price variation. With slightly abusing notation I keep using q_{it} for the resulting quasi-quantities. Next, I follow De Loecker, Goldberg, Khandelwal, & Pavcnik (2016) and use product-level price information to also control for input price variation across firms. Specifically, I estimate the following production function:

$$q_{it} = \widetilde{\boldsymbol{\phi}}'_{it}\boldsymbol{\beta} + B_{it}(.) + g_{it-1}(.) + \varepsilon_{it} + \xi_{it}. \tag{4.10}$$

Comments on the notation are in order.[71] $B_{it}(.) = B_{it}\big((\pi_{it}, ms_{it}, G_{it}, D_{it}) \times \boldsymbol{\phi}^{c}_{it}; \boldsymbol{\beta}\big)$ 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}). $\boldsymbol{\phi}^{c}_{it} = \{1; \widetilde{\boldsymbol{\phi}}_{it}\}$ contains two vectors. $\widetilde{\boldsymbol{\phi}}_{it}$ includes the same input terms as $\boldsymbol{\phi}_{it}$, either given in monetary terms and deflated by an industry-level deflator or already reported in quantity terms. The tilde indicates that some variables in $\widetilde{\boldsymbol{\phi}}_{it}$ are not expressed in true quantities (capital and intermediate inputs in my case).[72] The constant entering $\boldsymbol{\phi}^{c}_{it}$ highlights that elements of $B(.)$ enter the price control

[70] I define the production function as: $q_{it} = \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} + \beta_{ll} l^2_{it} + \beta_{mm} m^2_{it} + \beta_{kk} k^2_{it} + \beta_{lk} l_{it} k_{it} + \beta_{lm} l_{it} m_{it} + \beta_{km} k_{it} m_{it} + \beta_{lkm} l_{it} k_{it} m_{it} + \omega_{it} + \varepsilon_{it}$. The output elasticities of labor is given by: $\frac{\partial q_{it}}{\partial l_{it}} = \beta_l + 2\beta_{ll} l_{it} + \beta_{lk} k_{it} + \beta_{lm} m_{it} + \beta_{lkm} l_{it} m_{it}$. Changes in firms' output elasticities reflect a repositioning of firms on their production function.

[71] The estimation routine closely follows Mertens (2018), to whom I refer for further discussions.

[72] The calculation of capital stocks follows Bräuer, Mertens, & Slavtchev (2019). I explain their approach in Appendix C.9.

function linearly and interacted with $\widetilde{\boldsymbol{\phi}}_{it}$ (a consequence of using a translog production function).

Including a firm-specific price control function deals with unobserved variation in input prices between firms that cannot be eliminated by using industry-level deflators. In the specification above, this encompasses price variation from unobserved differences in firms' input quality, location, and four-digit industry affiliation.

In the spirit of Olley & Pakes (1996) and Levinsohn & Petrin (2003), $g_{it}(.) = g_{it}(e_{it}, k_{it}, l_{it}, \boldsymbol{z}_{it}) = \omega_{it}$ defines a productivity control function which addresses the well-known endogeneity problem, resulting from the dependence of firms' input decision on productivity. Here, e_{it} symbolizes firms' consumption of raw materials and energy inputs. $\boldsymbol{z}_{it}$ captures state variables of the firm that in addition to capital and labor influence demand for e_{it} and affect productivity. In my case, this includes a dummy variable for export activity, firm-level import competition (as defined in section 4.5), the number of products a firm produces, and the average wage it pays. Including those variables into $g_{it}(.)$ allows for learning and competition effects from import competition and export market participation as well as for (dis)economies of scope to affect firm productivity and demand for e_{it}. Furthermore, including wages into $g_{it}(.)$ captures variation in input prices that shifts firms' demand for raw materials and energy (De Loecker & Scott (2016)).[73]

Finally, ξ_{it} denotes the innovation in productivity which is Hicks-neutral and follows a Markov process that can be affected by firm actions captured in $\boldsymbol{z}_{it}$. Thus, we have: $\omega_{it} = \omega_{it-1} + \xi_{it} = g_{it-1}(.) + \xi_{it}$. Given my timing assumptions above, ξ_{it} is uncorrelated with firms' input decisions for capital and labor. Firms' input decisions for intermediate inputs,

[73] I approximate $g_{it}(.)$ with a third order polynomial in all of its elements, except for the variables in $\boldsymbol{z}_{it}$. Those I add linearly. $B_{it}(.)$ is approximated with a flexible polynomial where I 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. This is similar to the implementation in De Loecker et al. (2016).

however, are affected by ξ_{it}. Therefore, I rely on lagged values of intermediate inputs and their interactions as instruments to identify the associated coefficients. Similarly, I use lagged values of terms containing the firm's market share or output price index to identify the corresponding coefficients. This allows for prices to be adjusted in response to productivity shocks.

I estimate the production function using a one-step estimator as in Wooldridge (2009). The identifying moments are given by:

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

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 $g_{it}(.)$, and lagged interactions of the output price index with production inputs.[74]

I estimate (4.10) separately for individual NACE rev. 1.1 two-digit industries. Across all industries, mean (median) output elasticities for capital, labor, and intermediate inputs respectively are 0.63 (0.63), 0.28 (0.28), and 0.11 (0.10). I report detailed results from the production function estimation in Appendix C.3.

Having estimated the production function, I can calculate firm-level product and labor market power parameters as well as the contribution of firm market power to changing labor shares by using equations (4.4), (4.6), and (4.8).[75] To account for measurement error when calculating μ_{it} and γ_{it}, I apply the error correction of De Loecker & Warzynski (2012), i.e. I project output on a polynomial of variables in $\widetilde{\boldsymbol{\phi}}_{it}$, $B_{it}(.)$, and $g_{it}(.)$ and use the residuals of

[74] To save space, I delegated a formal definition of $\boldsymbol{\Upsilon}_{it}$ to Appendix C.4. There, I also show that estimating the production function by OLS yields similar results.

[75] 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 θ_{it}^{L} and ψ_{it}.

this auxiliary regression as a correction factor in equations (4.4) and (4.5) (for details see De Loecker & Warzynski (2012)). To ensure that I can compare aggregate statistics, I only keep firms with information for all components of equation (4.6). The final sample consists of 177,957 firm-year observations, for which Appendix C.3 summarizes key variables of this article.

4.4 Descriptive evidence

This section presents descriptive evidence on the evolution of labor shares, output elasticities, and product and labor market power parameters. Section 4.4.1 starts with an econometric evaluation of equation (4.6), showing that the framework of this article explains nearly the entire cross-sectional variation in firm- and industry-level labor shares. Following this, section 4.4.2 investigates how variables of equation (4.6) change over time. Section 4.4.3 dissects the movements of those variables into within and between-firm changes. Finally, section 4.4.4 discusses the extent to which market inefficiencies and efficient changes in production processes explain the documented change in the labor share.

4.4.1 Evaluating the theory with the data

By taking logs from equation (4.6) one receives a simple econometric model that can be empirically evaluated:

$$\ln(LS_{it}) = \beta_{\theta^L}\ln(\theta^L_{it}) + \beta_\mu \ln(\mu_{it}) + \beta_\gamma \ln(\gamma_{it}), \tag{4.12}$$

where I expect to estimate: $\beta_{\theta^L} = 1$ and $\beta_\mu = \beta_\gamma = -1$.

Table 4.1 presents the associated results from estimating equation (4.12) at the firm level. Note that I do not intend to present causal evidence. Instead, this empirical exercise shall simply i) validate that the relations derived above hold and ii) highlight the importance of accounting for labor market power when analyzing relationships between firms' product market power and labor shares.

Table 4.1

LABOR SHARES, MARKET POWER, AND LABOR OUTPUT ELASTICITIES, FIRM-LEVEL ANALYSIS			
	LS_{it} (1)	LS_{it} (2)	LS_{it} (3)
θ_{it}^L	0.425*** (0.00407)	0.624*** (0.00626)	0.987*** (0.00180)
μ_{it}	1.867*** (0.0144)	1.462*** (0.0161)	-0.913*** (0.00822)
γ_{it}	-	-	-0.979*** (0.00213)
Time FE	NO	YES	NO
Firm $*$ Industry FE	NO	YES	NO
Observations	177,957	170,482	177,957
R-squared	0.591	0.952	0.940
Number of firms	37,915	31,018	37,915

Notes: Table 4.1 reports results from estimating equation (12) at the firm level. Standard errors are clustered at the firm level. Stars indicate whether coefficients are significantly different from one for θ_{it}^L and from minus one for μ_{it} and γ_{it}. Significance: *10 percent, **5 percent, ***1 percent.

Columns 1 and 2 show results obtained from a model featuring perfect labor markets, i.e. where $\gamma_{it} = 1$ and $\ln(\gamma_{it}) = 0$. When not accounting for labor market power, I find that firms' product market power, μ_{it}, is positively correlated with their labor shares, even after controlling for several fixed effects. Only after conditioning on γ_{it} the sign of the coefficient on μ_{it} becomes, as predicted by equation (4.6), negative (columns 3). This change in the coefficient on μ_{it} implies that firms with high product market power, share their higher rents extensively with their employees, leading to *higher* labor shares within firms with higher product market power.[76] Thus, a model with perfect labor markets ignores an important mechanism connecting product market power with labor shares through rent-sharing processes. A model which abstracts from this mechanism "only" accounts for 60 percent of cross-sectional variation in labor shares (column 1). In contrast, after including γ_{it} (column

[76] A theoretical foundation of that result can be found in Nickell (1999).

3), the explaining power of the regression model increases to 94 percent (without any fixed effects). Although the coefficients are significantly different from one and minus one (due to small standard errors), they fit the parsimonious framework above extremely well.

To explore the relationship between labor shares and market power also graphically, Figure 4.2 plots weighted averages of LS_{it}, μ_{it}, and γ_{it} at the four-digit industry-level pairwise against each other. In line with the regression results, the unconditional scatter plots in Figure 4.2 show that labor shares are positively (negatively) associated with product (labor) market power parameters, whereas firms' labor and product market power are negatively correlated. Together those findings support the existence of rent-sharing in the German manufacturing sector.

MARKET POWER AND LABOR SHARES

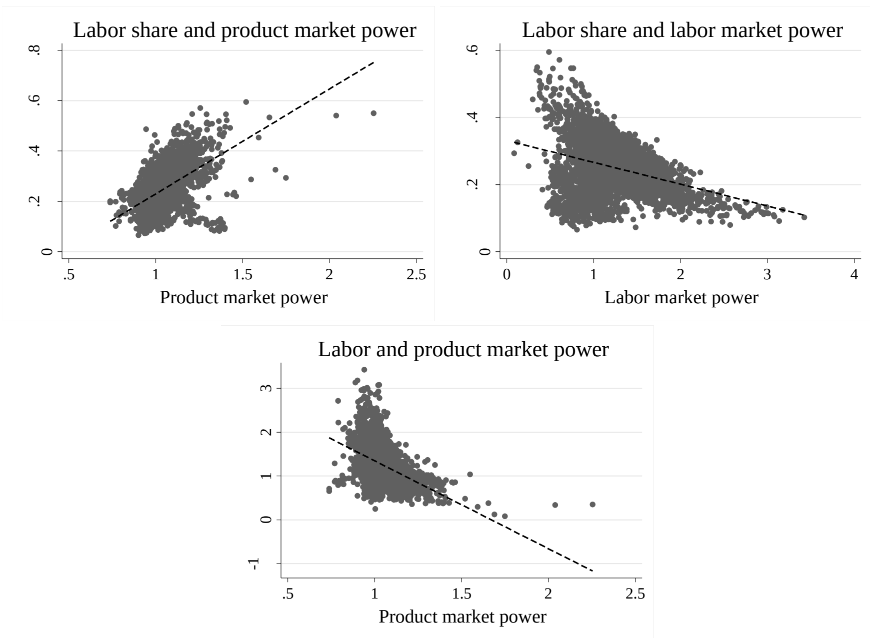

FIGURE 4.2 – Correlation between industry-level labor shares, product market power parameters, and labor market power parameters for four-digit industries with at least three firms. Germany's manufacturing sector. Sample firms.

Given the recent debate on the "rise of market power" and its implication for the labor share (see De Loecker & Eeckhout (2018) and De Loecker et al. (2018)), the finding of a positive correlation between firms' product market power and labor shares, both at the firm and the more aggregate industry level, is striking. When measuring market power, the existing literature typically assumes competitive labor markets. My results demonstrate that this might misguide conclusions on the relationship between product market power and labor shares, as firms with high product market power might share their higher rents with their workforce.

4.4.2 Aggregate movements

To aggregate variables, I use revenue weights throughout this article. This exploits that the aggregate revenue wage share can be decomposed in the following way:

$$LS_{jt} = \frac{\sum_i w_{it} L_{it}}{\sum_i P_{it} Q_{it}} = \sum_i \frac{P_{it} Q_{it}}{\sum_i P_{it} Q_{it}} * \frac{w_{it} L_{it}}{P_{it} Q_{it}}, \tag{4.13}$$

where j denotes the aggregation level (i.e. manufacturing sector) and sums are taken over all firms within j. Figure 4.3 shows the evolution of manufacturing sector wide aggregates of firm-level labor shares, output market power, labor market power, and labor output elasticities. Over the entire observations period the revenue labor share decreased from 26.8 to 23.6 percentage points. Instead of being associated with a change in a single component of equation (4.6), the fall of the labor share coincides jointly with a fall of the output elasticity of labor and a rise in aggregate product and labor market power. The clear negative time trend of labor's output elasticity over two decades severely questions the assumption of constant output elasticities, frequently applied in Cobb-Douglas production models. The crucial implication of this finding is that production models featuring constant output elasticities produce potentially biased measures of, among others, productivity and misallocation.

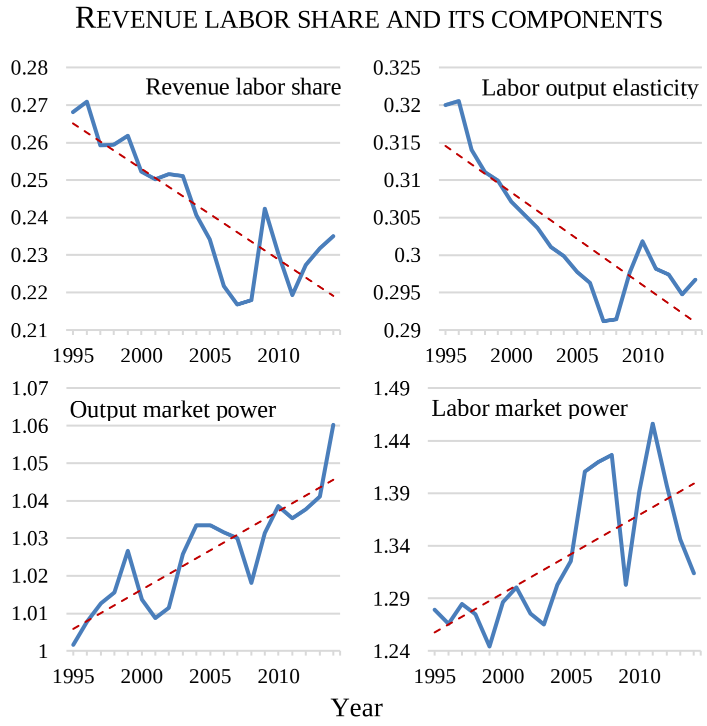

FIGURE 4.3 – Aggregates of firm-level labor shares, output elasticities of labor, output market power parameters, and labor market power parameters. Red dashed lines show linear trends. Germany's manufacturing sector. Sample firms.

To investigate more into the evolution of output elasticities, I discuss the movements of labor, capital, and intermediate input output elasticities at the two-digit sector level in Appendix C.5. Most notably, I find that industry-level output elasticities of labor and intermediates also exhibit clear time trends, while output elasticities of capital are more stable. Whereas labor output elasticities decrease, intermediate input output elasticities increase over the observation period. Jointly this suggest an increasing importance of intermediate inputs in firms' production activities that induces a substitution of labor for intermediate inputs. 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 (e.g. Sinn (2006); Goldschmidt & Schmieder (2017)). Notably, a substitution of labor for intermediate inputs also increases the importance of capital relative to labor in firm's production processes. For more details, please see Appendix C.5.

With respect to the market power parameters, I find a clear upward trend in both. Compared to the findings of De Loecker & Eeckhout (2018), however, the product market power levels I estimate are lower. Note that my estimates even suggest that product markets where competitive in 1995. The reasons for the differences in output market power levels between De Loecker & Eeckhout (2018) and this study is a consequence of De Loecker and Eeckhout applying a different production model featuring competitive input markets. De Loecker and Eeckhout estimate a production model with gross output on the left-hand side and capital and a joint production factor capturing "variable" inputs (including labor) on the right-hand side of the production function. If the input market for this variable factor is imperfect, the resulting market power parameter reflects market power in output *and* in the variable factor's input market. Hence, in the presence of imperfect labor markets, the measure of De Loecker and Eeckhout is a combination of firms' output and labor market power. As Figure 4.3 shows positive and increasing levels of firms' labor *and* product market power, product market power as measured in De Loecker & Eeckhout (2018), would be higher and more strongly increasing in my case.

While I find that aggregate product market power is low, I document a high level of aggregate firm labor market power in Germany' manufacturing sector. Hence, imperfect functioning labor markets are a more relevant source of market power for German manufacturing sector firms' than product market imperfections. This finding is striking, given that i) most existing work in the IO literature abstracts from labor market power and focusses on market power in product markets and ii) policy measures to address each type of market power differ.

Intuitively, the rise of labor market power in the early 2000s could be a result of Germany's major labor market reforms (i.e. the "Hartz-reforms"), which decreased unemployment benefits, whereas the fall of labor market power after the crisis could be an early sign of a skill shortage. Moreover, the general increase in firms' labor market power coincides with the fall in the union coverage/density over several decades in Germany (e.g. Dustmann, Fitzenberger, Schönberg, & Spitz-Oener (2014); OECD (2017); Hirsch & Müller (2018)).

With respect to the business cycle, firms' product market power shows a slightly countercyclical or acyclical movement, whereas firms' labor market power behaves cyclical. The latter is very intuitive as labor market power captures the difference between the revenue contribution of labor and its compensation. If, for instance, due to labor hoarding during the crisis, labor expenditures are not perfectly downward adjusted in response to output losses, labor's revenue product will decrease stronger than its compensation (which lowers γ_{it}). This is exactly what we see in Figure 4.2 during 2009.

4.4.3 Between- vs. within-firm changes

The weighted average, x_{jt}, of any variable x_{it} can be decomposed in the following way:

$$x_{jt} = \sum_i s_{it} x_{it} = \bar{x}_{jt} + cov_{jt}(x_{it}, s_{it}), \quad (4.14)$$

where $s_{it} = \frac{P_{it}Q_{it}}{\sum_i P_{it}Q_{it}}$, $\bar{x}_{jt}$, and $cov_{jt}(x_{it}, s_{it})$ respectively denote the weight of economic activity (revenue weights), the unweighted average of x_{it} across firms, and the covariance between x_{it} and s_{it} (Olley & Pakes (1996)). Changes in the unweighted average reflected within-firm changes, while changes in the covariance reflect between-firm changes (i.e. reallocation). Figure 4.4 illustrates this decomposition graphically for the aggregates of LS_{it}, θ_{it}^{L}, μ_{it}, and γ_{it}. Panel A plots unweighted averages (within-firm contribution), whereas Panel B shows the associated covariance term (between-firm contribution).

WITHIN-FIRM VS. BETWEEN-FIRM CHANGES

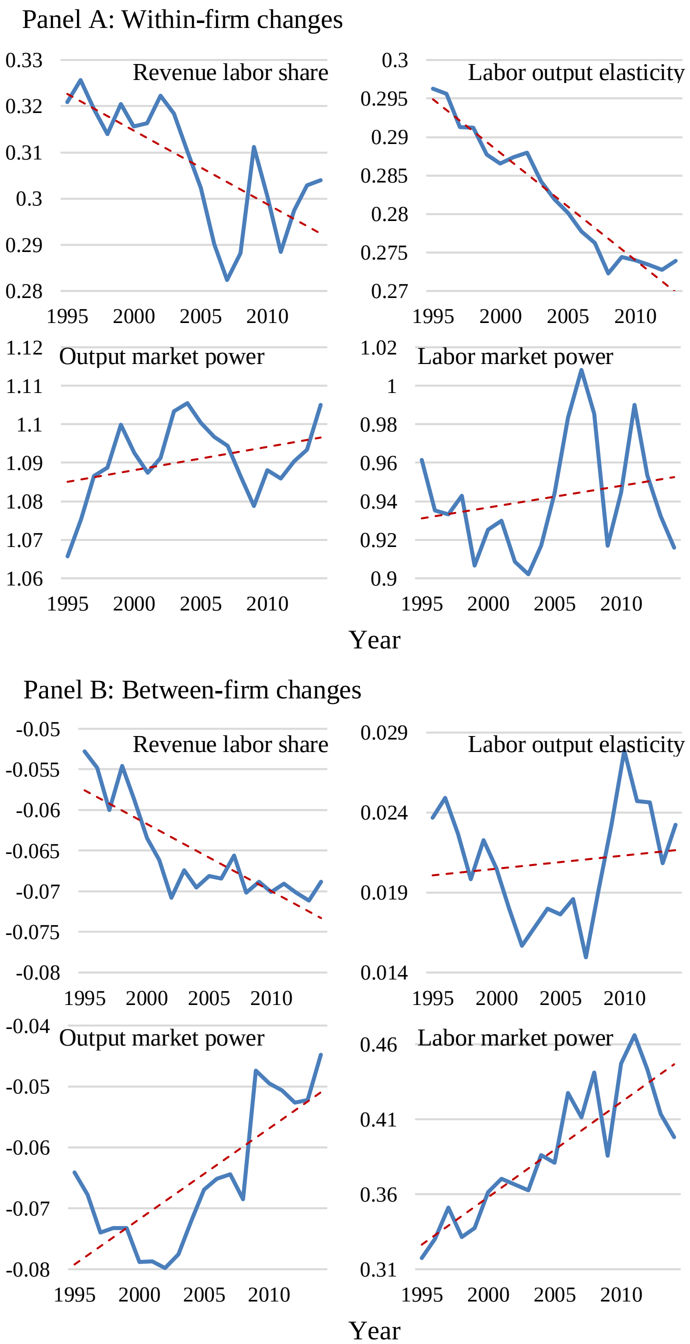

FIGURE 4.4 – Aggregates of firm-level labor shares, output elasticities of labor, output market power parameters, and labor market power parameters, within- and between-firm decomposition. Red dashed lines show linear trends. Germany's manufacturing sector. Sample firms.

The decline in the labor share has both, a strong within- and between-firm component. In contrast, the decline in the aggregate output elasticity of labor is a within-firm phenomenon, suggesting that it is driven by factors that influence most manufacturing firms similarly. The between-firm component is negative for the labor share and product market power parameter, while slightly positive (but close to zero) for labor's output elasticity and strongly positive for the labor market power parameter. This implies that *larger* firms have lower labor shares, less product market power, slightly higher output elasticities of labor, and clearly higher labor market power levels than smaller firms.[77] Interestingly, the unweighted average of the labor market power parameter is below one, implying that employees have a strong position within most firms. A larger part of economic activity, however, is concentrated in firms with high labor market power, leading to an aggregate labor market power parameter above one.

Table 4.2

RELATIVE CHANGES IN THE AGGREGATE LABOR SHARE, LABOR OUTPUT ELASTICITY, AND MARKET POWER PARAMETERS, WITHIN- VS. BETWEEN-FIRM CHANGES

Period	Labor share			Output elasticity of labor		
	ΔLS_{jt} (1)	Within contribution (2)	Between contribution (3)	$\Delta\theta_{jt}^{L}$ (4)	Within contribution (5)	Between contribution (6)
1995-2000	-5.92%	-1.93%	-3.98%	-4.02%	-3.03%	-0.99%
2000-2005	-7.12%	-5.27%	-1.85%	-3.04%	-2.10%	-0.94%
2005-2010	-1.61%	-0.77%	-0.83%	+1.39%	-2.06%	+3.44%
2010-2014	+2.00%	+1.46%	+0.54%	-1.72%	-0.17%	-1.54%
1995-2014	-12.31%	-6.31%	-6.00%	-7.27%	-7.12%	-0.15%

Period	Product market power			Labor market power		
	$\Delta\mu_{it}$ (7)	Within contribution (8)	Between contribution (9)	$\Delta\gamma_{jt}$ (10)	Within contribution (11)	Between contribution (12)
1995-2000	+1.21%	+2.69%	-1.47%	+0.61%	-2,81%	+3.42%
2000-2005	+1.94%	+0.77%	+1.17%	+3.01%	+1.47%	+1.54%
2005-2010	+0.50%	-1.19%	+1.69%	+5.02%	+0.02%	+5.00%
2010-2014	+2.08%	+1.63%	+0.45%	-5.60%	-2.07%	-3.54%
1995-2014	+5.85%	+3.93%	+1.93%	+2.74%	-3.57%	+6.31%

Notes: Table 4.2 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.

To give a quantitative impression, I calculate the contribution of within- and between-firm dynamics to changes in weighted aggregates for the variables of interest in Table 4.2. For every variable, the first column reports the relative change in its aggregate value, while the second and third columns show the within- and between-firm contribution to the total change. For instance, the aggregate labor share declined by 6.31% (6.00%) due to within- (between-)

[77] In Appendix C.7, I show that the relationships between firm size and my variables of interest are robust to defining firms' share of economic activity as employment share.

firm dynamics. Thus, the aggregate labor share fell by $6.31\% + 6.00\% = 12.31\%$, showing that its decline is equally driven by within- and between-firm dynamics.

For output market power, two thirds of the increase are a result of within-firm changes, whereas the remaining one third results from reallocation processes between firms. With respect to labor market power, the reported changes mask the fluctuations and the general upward trend in labor market power depicted in Figure 4.3. Note that in 2014 the within-firm component of labor market power is even below its initial level. This decrease, however, is dominated by a reallocation of economic activity towards high-labor-market-power-firms.

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

Using equation (4.8) and aggregating as beforehand, Figure 4.5 shows how the aggregate wedge between the labor share and the output elasticity of labor, ψ_{jt}, evolved over the period 1995-2014. The level of ψ_{jt} is depicted on the left vertical axis. The evolution of ψ_{jt}, which is represented by the blue solid line, reflects the extent to which factors other than changing output elasticities can account for the observed decline in labor's share. Through the lens of this study's framework, this corresponds to changes in firms' product or labor market power.

Already in 1995, labor shares were below their counter factual level of competitive output and input markets. Over the following two decades this wedge displays a clear negative time trend, i.e. the wedge widens. There could be several events explaining this increase in market distortions between 1995-2014. Besides the mentioned introduction of labor market reforms in 2005 or the erosion of labor market institutions starting in the 90s, increased globalization could also have contributed to a rise in market distortions. In particular, an increase in the share of imported foreign intermediate inputs could have led to a substitution of domestic with foreign workers, which could have weakened the bargaining power of the former (Rodrik (1997)). Simultaneously, the availability of cheaper foreign inputs could have led to an increase in domestic product market power by an incomplete pass-through from cost savings to output prices (De Loecker et al. (2016)). Alternatively, rising export demand could have increased domestic firms' profits without an associated increase in domestic wages, also leading to an increase in firms' labor market power (Mertens (2018)). Apart from this, rising market concentration through modern technologies (e.g. digital platforming or online search engines) that transform markets into "the-winner-takes-it-all-industries" could have contributed to an increase in product and labor market power (Autor et al (2017); Van Reenen (2018)). Naturally, a full investigation of all potential changes in the economic environment that impact on the labor share and its components is beyond the scope of this article. However, to address this interesting question at least to some extent, I investigate how final product import competition and export demand affect LS_{it}, θ_{it}^{L}, μ_{it}, and γ_{it} in the next section.

Beforehand, note that in comparison with Figures 4.3 and 4.4, one discovers an astonishing similarity between movements in aggregate labor market power and ψ_{jt}. To highlight this, the dashed black line of Figure 4.5 displays the invers of the aggregate labor market power parameter (levels are represented on the right vertical axis). The striking similarity between movements in ψ_{jt} and γ_{it} points to a key role for labor market power fluctuations in explaining fluctuations in ψ_{jt}.

In recent years, market power distortions reduced again, such that over the entire observation period ψ_{jt} decreased by one point, i.e. observed labor shares in 2014 are roughly 1 percentage point further below the counter factual labor share level of competitive markets than in 1995. This implies that increasing product and labor market power account for 30% of the entire 3.3 percentage point decline in the labor share over the period 1995-2014. Hence, the remaining 70% can be explained by changes in firms' production processes (output elasticities of labor dropped from 0.320 to 0.297).

Still, from a social planner's point of view, the increase in market power suggests room for policies that simultaneously raise aggregate economic output and labor's share of it by targeting firms' market power. This is clearer for the rise in labor market power than for the increase in product market power because in the presence of sunk research costs there exists a socially optimal level of product market power, necessary to recover costs from creating a new variety (given that consumers value innovations sufficiently). Thus, if entry or innovation costs increased sufficiently strong, the documented trend in product market power could be necessary to create a socially beneficial level of innovation.

Nevertheless, this logic does not hold for the increase in firms' *labor* market power as workers, which are not necessary the consumers of the final good, should not carry the burden of refinancing sunk costs of product innovations. Furthermore, recap that from comparing μ_{it} with γ_{it},we know that the major part of market power distortions in Germany's manufacturing sector results from high and increasing levels of firms' labor market power. Hence, the room for policies targeting labor market power is higher than for policies targeting product market power.

Guiding policies in consideration of high and increasing labor market power levels naturally depends on a variety of aspects, including normative discussions on preferences (e.g. for inequality). If political decisions makers, however, agree on targeting firms' labor market power, the design of an appropriate policy will depend on the underlying distribution of market power across firms. In case of Germany, for instance, I document that the average firm has no market power in its labor markets. The high and increasing level of aggregate labor market power instead results from a positive and increasing covariance between firms' share of economic activity and their labor market power. Consequently, policies targeting all firms equally or small firms especially are unsuitable to reduce aggregate labor market power in

Germany's manufacturing sector (some may argue that a uniform minimum wage could be an example of such a policy). A policy to reduce firms' labor market power could instead be an extension of the existing legislative antitrust analysis, which currently mostly focusses on market power in product markets, to also consider the effects of labor market power (Naidu et al. (2018)).

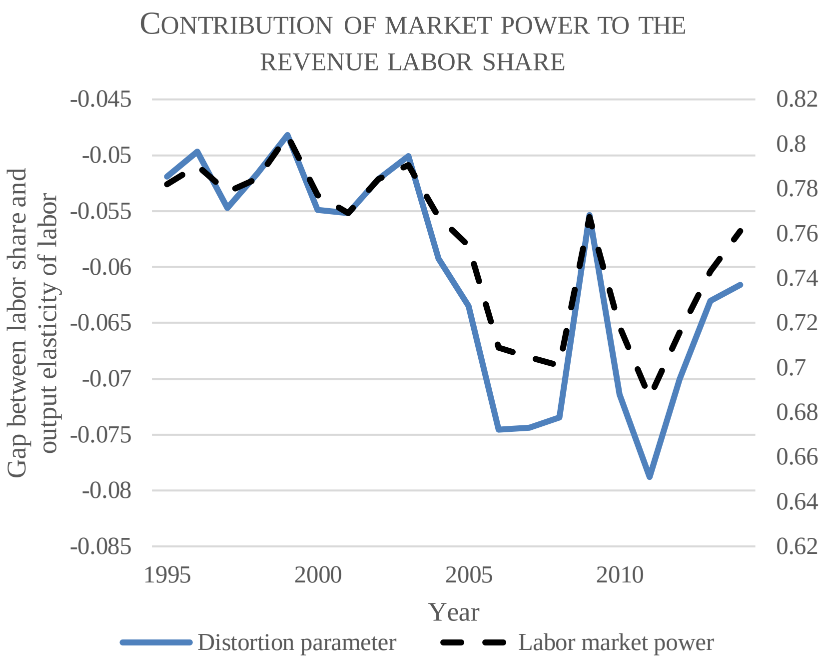

FIGURE 4.5 – Aggregate labor market power and the aggregate wedge between the observed labor share and the counterfactual labor share under counterfactually competitive product and labor markets. Germany's manufacturing sector. Sample firms.

4.5 The role of international competition and demand

This section discusses the extent to which final product trade affects labor shares, market power, and output elasticities of labor. Section 4.5.1 describes the empirical approach and runs a firm-level analysis on the effects of Chinese import competition and export demand on the variables of interest. As this analysis focusses on within-firm effects, section 4.5.2 complements it by investigating the between-firm reallocation processes induced by international trade.

4.5.1 Firm-level labor shares and trade shocks

Having established that a major part of the decline of Germany's manufacturing sector labor share can be explained by a declining output elasticity of labor, it is now interesting to investigate how changes in the economic environment impact on the labor share and its drivers. Within this context, a large body of literature discusses the relative importance of globalization in explaining falling labor shares.[78] To shed new light on this debate, I exploit the firm-product dimension of the AFiD-data to construct measures of *final product* import competition and export opportunities for each individual firm.[79]

Intuitively, international competition has the potential to affect all components of our simple framework. On the one hand, international trade affects firms' rents, which in the presence of imperfect functioning labor markets might affect firms' labor market power (e.g. Mertens (2018)). On the other hand, final product trade may lead to adjustments in firms' product mix or product prices, translating into changes in firm productivity and markups (e.g. Melitz, Mayer, & Ottaviano (2014)). Moreover, besides setting incentives for firms to invest in modern technologies, exposure to international competition gives an impetus for reorganizing existing production structures, potentially affecting the importance of labor to firms (e.g. Caliendo, Monte, & Rossi-Hansberg (2017); Antras, Fort, & Tintelnot (2017)).

To measure import competition and export opportunities, I combine the AFiD data with the United Nations Comtrade Database (Comtrade). I then follow Mion & Zhu (2013) and define a measure of product-level import competition as:

[78] E.g. Elsby et al. (2013); Karabarbounis & Neiman (2014); Acemoglu & Restrepo (2016); Doan & Wan (2017); Muendler (2017); Gupta & Helble (2018).
[79] I focus on final product trade measures as I do not have information on imported intermediate products at the firm level. It is likely that final and intermediate product trade affect my variables of interest differently (De Loecker & Goldberg (2014); Wang, Wei, Yu, & Zhu (2018)).

(4.15) $$IM_{gt}^{CHN \rightarrow GER} = \frac{M_{gt}^{CHN \rightarrow GER}}{M_{gt} + Y_{gt}} * 100,$$

where $M_{gt}^{CHN \rightarrow GER}$ measures product-level trade flows from China to Germany, and M_{gt} and Y_{gt} respectively denote German world imports and total observed domestic production of product g.[80] Similarly, I define a measure of export opportunities as:

(4.16) $$EX_{gt}^{GER \rightarrow CHN} = \frac{E_{gt}^{GER \rightarrow CHN}}{M_{gt} + Y_{gt}} * 100,$$

where $E_{gt}^{GER \rightarrow CHN}$ denotes product exports flowing from Germany to China. I aggregate $IM_{gt}^{CHN \rightarrow GER}$ and $EX_{gt}^{GER \rightarrow CHN}$ to the firm level using revenue weights. Specifically, for every firm-product-year combination I first multiply $IM_{gt}^{CHN \rightarrow GER}$ and $EX_{gt}^{GER \rightarrow CHN}$ with the firm-specific sales of product g divided by the firm's total product market sales. This weights product-level trade flows with their importance to the firm. Subsequently, I sum across all weighted product trade flows within a firm. I denote the resulting trade measures by IMP_{it}^{CHN} and EXP_{it}^{CHN}.

To estimate the effect of international trade on labor shares and its components, I run the following regression:

(4.17) $$\ln(y_{it}) = \beta_{IMP} IMP_{it-1}^{CHN} + \beta_{EXP} EXP_{it-1}^{CHN} + \boldsymbol{C}_{it-1}' \boldsymbol{\beta} + \vartheta_t + \vartheta_{ij},$$

where $y_{it} = \{LS_{it}, \theta_{it}^{L}, \mu_{it}^{M}, \gamma_{it}\}$. The vector $\boldsymbol{C}_{it}'$ controls for a firm's capital over labor ratio, value-added over revenue ratio, and number of products. ϑ_t and ϑ_{ij} control for time and firm times industry fixed effects. Thus, equation (4.17) specifies a within-firm estimator.

[80] AFiD collects product-level production information for all manufacturing sector plants/firms with at least 20 employees within Germany. I do not use information on exports when defining the import competition measure as in some cases exports reported in Comtrade exceed domestic production in AFiD. Reasons for that could be differences in reporting days or the fact that AFiD contains production information only for all plants with at least 20 employees.

Consistent with the production model described in section 4.3, I rely on lagged trade measures to allow for a time frame in which adjustment processes can be realized.

An extensive literature documents that regressing labor market outcomes on trade measures like (4.15) and (4.16) suffers from an endogeneity problem because unobserved demand and supply shocks might simultaneously affect the dependent and independent variable (see Autor et al. (2013) and Dauth et al. (2014) for a discussion). To address this problem, I follow the dominant IV strategy in the literature and use trade flows between China and countries similar to Germany as instruments for IMP_{it}^{CHN} and EXP_{it}^{CHN}. Specifically, I define instruments from imports (exports) flowing from China (instrument group countries) to instrument group countries (China) over total imports (exports) flowing from the world (instrument group) to the instrument group (world):

(4.18) $$EX_{gt}^{INS} = \frac{E_{gt}^{INS \rightarrow CHN}}{E_{gt}^{INS \rightarrow WORLD}} * 100$$

and

(4.19) $$IM_{gt}^{INS} = \frac{M_{gt}^{CHN \rightarrow INS}}{M_{gt}^{WORLD \rightarrow INS}} * 100.$$

Identical to the construction of IMP_{it}^{CHN} and EXP_{it}^{CHN}, I aggregate (4.18) and (4.19) to the firm level using revenue shares.[81] I report the first stage regression results for all following IV-specifications in Appendix C.6.

[81] The instrument country group includes Australia, New Zealand, Sweden, Norway, Japan, Great Britain, Canada, and Singapore. My results are unaffected from excluding good flows between Germany and the instrument country group in the denominator (results are available on request). One potential threat to my identification is that firms adjust their product mix in expectation of trade shocks, which would introduce an endogeneity problem when aggregating product-level trade flows to the firm level using revenue shares. I address this issue in Appendix C.8 by using time constant revenue weights in my aggregation. All results are qualitatively robust.

Table 4.3 reports results from estimating equation (4.17) by OLS and IV. Both estimators report a highly significant negative (positive) effect of export opportunities (import competition) on firm-level labor shares. According to the IV-results, a one unit increase in export opportunities (import competition) decreases (increases) labor shares within firms by 0.66 (0.24) percent.[82] To put those figures into perspective: Between 1995 and 2014 I observe a total increase in export demand (import competition) from China by 1.11 (1.14) points. Hence, the negative effect of increased export demand accounts for $\frac{0.66*1.11*100}{6.31} \approx 12$ percent of the fall in the aggregate within-firm labor share. However, the increase in import competition offsets this effect; such that the net contribution of increased trade with China to the total decline of the within-firm labor share equals roughly 7 percent.

[82] Mertens (2018) provides a rational for these findings by showing that profit gains and losses from trade are not perfectly passed through into labor expenditure adjustments within firms.

TABLE 4.3

LABOR SHARES, MARKET POWER PARAMETERS, LABOR OUTPUT ELASTICITIES, AND INTERNATIONAL TRADE

	OLS				IV			
	LS_{it}	θ_{it}^{L}	μ_{it}	γ_{it}	LS_{it}	θ_{it}^{L}	μ_{it}	γ_{it}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IMP_{it-1}^{CHN}	0.00224***	-0.00070	0.00053***	-0.00318***	0.00236***	-0.00112	-0.00001	-0.00406***
	(0.000500)	(0.00049)	(0.000180)	(0.00060)	(0.000828)	(0.000725)	(0.000280)	(0.000863)
EXP_{it-1}^{CHN}	-0.00179**	-0.00059	0.00116***	0.00006	-0.00664**	0.00166	0.00003	0.00777***
	(0.000738)	(0.00042)	(0.000252)	(0.000543)	(0.00251)	(0.00167)	(0.000821)	(0.00232)
Firm x Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES
Firm-level controls	YES	YES	YES	YES	YES	YES	YES	YES
Observations	114,060	114,060	114,060	114,060	114,060	114,060	114,060	114,060
R-squared	0.915	0.952	0.898	0.939	0.915	0.952	0.898	0.938
First-stage F-test	-	-	-	-	106.00	106.00	106.00	106.00
Number of firms	22,638	22,638	22,638	22,638	22,638	22,638	22,638	22,638

Notes: Table 4.3 reports results from estimating equation (4.17) by OLS and IV. OLS-results are reported in columns 1-4. IV-results are reported in columns 5-8. The dependent variable in columns 1-4 and 5-8 are respectively the revenue labor share, the output elasticity of labor, the output market power parameter, and the labor market power parameter. All regressions include time and industry times firm fixed effects and controls for the firm's, capital over labor ratio, value-added over revenue ratio, and number of products. Standard errors are clustered at the firm level. Significance: *10 percent, **5 percent, ***1 percent.

Notably, I cannot find any evidence for an associated change in labor output elasticities from international trade. This is striking as the decomposition exercise in section 4.4.3 shows that the aggregate output elasticity of labor decreased due to within-firm dynamics, which is exactly what the within-firm-specification in equation (4.17) should capture. Seemingly, factors other than final product trade cause the within-firm change in labor's output elasticity.

Interestingly, both, IV- and OLS- results, document that import competition affects firms' labor market power negatively. The estimators depart, however, with respect to the other coefficients on μ_{it} and γ_{it}. When using OLS, I find a significant positive effect of both trade measures on firms' product market power. While I cannot validate this result by IV, IV-results show a positive impact of export opportunities on labor market power within firms, which cannot be found using OLS. Given the potential presence of an endogeneity problem in my OLS-estimates, I prefer the IV-specification. Yet, although both estimators depart with respect to the type of market power affected, the result that final product trade affects firms' labor shares through changes in their market power holds regardless of the estimation technique.

4.5.2 Reallocation of economic activity between exporters and non-exporters

Recap that the labor share decomposition in section 4.4.3 shows that only half of the decline in the aggregate manufacturing sector labor share is driven by falling within-firm labor shares. By design, estimating the effect of trade on labor shares as above cannot account for the large part of the change in the manufacturing sector labor share resulting from a between-firm reallocation process. Moreover, although the within-firm component of labor market power displays a positive trend, labor market power mainly rose due to between-firm dynamics. However, the within-firm specification in equation (4.17) is exactly what allows me to draw causal inferences on how changes in trade flows affect changes in the outcomes of interest. Transferring the analysis in an alternative approach to the industry level would introduce several inaccuracies because i) firms are active in multiple industries simultaneously and ii) industry-level trade measures mix up final product and intermediate product trade flows.

TABLE 4.4

SUMMARY STATISTICS,
EXPORTER VS. NON-EXPORTER

	Exporter			Non-exporter		
	Mean	Median	N	Mean	Median	N
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Employees	252.78	107	135,730	115.13	59	42,227
Log of value-added per employee	16.54	16,42	135,730	15.59	15.44	42,227
Deflated capital per employee in thousands	98,674	73,776	135,730	86,214	51,079	42,227
Deflated intermediates per employee in thousands	94,209	74,768	135,730	64,814	46,699	42,227
Value-added over revenue	0.40	0.40	135,730	0.44	0.44	42,227
Average real wage	34,771	34,450	135,730	26,941	26,237	42,227
Revenue labor share	0.30	0.29	135,730	0.33	0.33	42,227
Value-added labor share	0.77	0.75	135,730	0.78	0.77	42,227
Output market power parameter	1.09	1.07	135,730	1.10	1.08	42,227
Labor market power parameter	0.99	0.91	135,730	0.77	0.68	42,227
Output elasticity of labor	0.29	0.29	135,730	0.25	0.25	42,227

Notes: Table 4.4 reports mean and median values of selected variables separately for exporting and non-exporting firms. Means, medians, and the number of observations used to calculate the statistics are respectively reported in columns 1 and 4, 2 and 5, and 3 and 6.

To still shed light on the reallocation process induced by trade, I investigate how the shares of economic activity of exporting and non-exporting firms change in response to final product trade. To motivate this exercise, Table 4.4 reports mean and median values for selected variables separately for exporting and non-exporting firms. There are several interesting things to note. Exporting firms are larger, have a higher labor productivity, and use more capital and intermediate inputs per employee than non-exporting firms. As expected, exporting firms also pay higher wages. Yet, exporting firms are characterized by lower labor shares and higher labor market power compared to non-exporting firms. Note that exporting firms' high labor market power is not driven by low wages. It instead results from high marginal products of labor, which are potentially far above industry average wages. This supports the presence of a "hide-effect" in wage negotiations which refers to the observation that highly profitable firms "hide" behind industry-wide wage standards to pay wages below their workers' revenue contribution (Hirsch & Müller (2018)).

Notably, exporting and non-exporting firms do not differ in their output market power. If anything, non-exporting firms have slightly higher levels of μ_{it}. As there is a clear difference in labor shares and labor market power between exporting and non-exporting firms, a reallocation of domestic economic activity from non-exporting to exporting firms increases aggregate firm labor market power and decreases aggregate labor shares, ceteris paribus.

Table 4.5 presents results from estimating equation (4.17) separately for exporters (Panel A) and non-exporters (Panel B) using firms' share of employment and revenue in the associated sample totals, respectively denoted by $\frac{L_{it}}{\sum L_{it}}$ and $\frac{P_{it}Q_{it}}{\sum P_{it}Q_{it}}$, as dependent variables. Firms being hit by import competition reduce their share of economic activity. According to the IV-results, a one-point increase in import competition that an exporting firm experiences reduces its employment and revenue share by 0.8 and 1.3 percent, respectively. For non-exporters, those effects are larger, respectively with 1.2 and 2.5 percent. The key point is, however, that export opportunities leave non-exporting firms unaffected and exclusively increase exporters' employment and revenue shares. Hence, increasing foreign demand reallocates economic activity towards exporting firms, which are characterized by lower labor shares, higher labor market power, and higher output elasticities of labor. This offers a potential explanation for how international trade can contribute to the observed developments in the between-firm components of the aggregate labor share and labor market power parameter. Note, that the reallocation of economic activity towards (highly productive) exporting firms also suggests a potential channel for aggregate productivity gains as described in Melitz (2003). This points to a trade-off between aggregate gains in terms of productivity and a lower aggregate labor share resulting from trade induced reallocation processes.

TABLE 4.5

INTERNATIONAL TRADE AND THE REALLOCATION OF ECONOMIC ACTIVITY

Panel A: Exporter	OLS		IV	
	$\frac{L_{it}}{\Sigma L_{it}}$ (1)	$\frac{P_{it}Q_{it}}{\Sigma P_{it}Q_{it}}$ (2)	$\frac{L_{it}}{\Sigma L_{it}}$ (3)	$\frac{P_{it}Q_{it}}{\Sigma P_{it}Q_{it}}$ (4)
IMP_{it-1}^{CHN}	-0.00435***	-0.00820***	-0.00847***	-0.0134***
	(0.000869)	(0.00112)	(0.00150)	(0.00189)
EXP_{it-1}^{CHN}	0.00285***	0.00609***	0.0107***	0.0241***
	(0.000940)	(0.00147)	(0.00354)	(0.00466)
Firm x Industry FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Firm-level controls	YES	YES	YES	YES
Observations	88,787	88,787	88,787	88,787
R-squared	0.983	0.982	0.983	0.982
First-stage F-test	-	-	104.50	104.50
Number of firms	17,066	17,066	17,066	17,066
Panel B: Non-exporter	OLS		IV	
	$\frac{L_{it}}{\Sigma L_{it}}$ (1)	$\frac{P_{it}Q_{it}}{\Sigma P_{it}Q_{it}}$ (2)	$\frac{L_{it}}{\Sigma L_{it}}$ (3)	$\frac{P_{it}Q_{it}}{\Sigma P_{it}Q_{it}}$ (4)
IMP_{it-1}^{CHN}	-0.00927***	-0.0124***	-0.0126***	-0.0249***
	(0.00226)	(0.00319)	(0.00434)	(0.00610)
EXP_{it-1}^{CHN}	-0.00287	0.00578*	-0.00120	0.00534
	(0.00258)	(0.00312)	(0.0143)	(0.0225)
Firm x Industry FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Firm-level controls	YES	YES	YES	YES
Observations	23,556	23,556	23,556	23,556
R-squared	0.979	0.981	0.979	0.981
First-stage F-test	-	-	3.840	3.840
Number of firms	6,068	6,068	6,068	6,068

Notes: Table 4.5 reports results from estimating equation (4.17) by OLS and IV using separate samples for $t-1$ exporters (Panel A) and non-exporters (Panel B). OLS-results are reported in columns 1 and 2. IV-results are reported in columns 3 and 4. The dependent variable in columns 1 and 3 is the firm-level employment share in total employment of sample firms, whereas in columns 2 and 4 it is the firm-level sales share in total sales of sample firms. All regressions include time and industry times firm fixed effects and controls for the firm’s number of products, capital over labor ratio, and value-added over revenue ratio. Standard errors are clustered at the firm level. Significance: *10 percent, **5 percent, ***1 percent.

4.6 Conclusion

This article derives a parsimonious theory to shed light on potential mechanisms driving declining labor shares. The framework of this article offers three competing explanations for a fall in the labor share: an increase in firms' product market power, an increase in firms' labor market power, or a fall in firms' output elasticities of labor, which reflects a decreasing importance of labor in firms' production activities. While being based on a minimal set of assumptions, the applied framework explains 94% of observed variation in Germany's manufacturing sector labor share over the period 1995-2014.

Coinciding with the fall of the labor share, I document an increase in firms' product and labor market power. However, through the lens of this study's production side model, increasing product and labor market power can only account for 30% of the observed decline in the labor share. The remaining 70% are explained by a declining aggregate output elasticity of labor. Latter not only suggests a leading role for changing production processes in explaining the fall in Germany's manufacturing sector labor share; but it also raises doubts on production models featuring constant output elasticities.

When analyzing potential causes, I find that increasing import competition and export demand cannot explain the secular change in the output elasticity of labor. This suggest that other factors cause its fall. However, increasing foreign export demand (import competition) decreases (increases) firm-level labor shares by increasing (decreasing) labor market power within firms. Moreover, I find that a rise in foreign demand reallocates domestic economic activity towards large exporting firms, which are characterized by higher labor market power, higher labor productivity, and smaller labor shares.

Although the documented fall of Germany's manufacturing sector labor share is mostly driven by changes in firms' production processes, the high and increasing level of aggregate labor market power suggests room for policies that can simultaneously increase aggregate economic output and labor's share of it. A recently discussed example of such a policy is an extension of current antitrust regulations, which mostly focus on market power in product markets, to also consider the effects of labor market power (Naidu et al. (2018)).

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Appendix C

C.1 Two models of labor market power

In this section I derive two examples on how labor market imperfections translate into labor market power that can be measured by wedges between wages and marginal revenue products of labor. I start with discussing a simple efficient bargaining model in which employees possess labor market power. Following this, I present a model of monopsonistic labor markets. In both models, labor market power materializes in wedges between wages and marginal revenue products of labor. For a combination of both models, I refer the interested reader to Falch & Strøm (2007). Throughout this section, I heavily draw on Dobbelaere & Mairesse (2013).

Case 1: Employee-side labor market power – efficient bargaining model

Firms compete in imperfect product markets. As in Dobbelaere & Mairesse (2013), risk-neutral workers collectively bargain with the firm over wages (w_{it}) and employment (L_{it}). Ultimately, this coordination of labor supply, i.e. the absence of a competitive pool of workers that compete over firms' labor demand, will lead to employee-side labor market power.

Employees maximize their utility function, given by:

(C.1) $$U(w_{it}, L_{it}) = w_{it} L_{it} + (\bar{L}_{it} - L_{it})\bar{w}_{it} ,$$

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

As in the main text, firms produce output using the production function:

(C.2) $$Q_{it} = Q_{it}(.) = Q_{it}(L_{it}, K_{it}, M_{it}, e^{\omega_{it}}).$$

Capital is a fixed production input. For mathematical convenience I assume that labor and intermediate inputs are both flexible. This will limit the source of labor market power to pure bargaining power within the Nash-bargaining process between firms and employees (e.g. due to the presence of unions). However, generally, one can additionally allow for inflexible contracts to create employee-side labor market power by defining that a part of the wage bill cannot be adjusted in the short-run.[83] With $R_{it} = P_{it}Q_{it}$ denoting revenue, this implies that firms maximize the following short-run objective function:

(C.3) $$\Pi_{it} = R_{it} - w_{it}L_{it} - z_{it}M_{it}\ ,$$

where z_{it} denotes the unit costs for intermediate inputs. Intermediate input markets are perfectly competitive. Thus, firms can unilaterally set M_{it} given z_{it} (this is not necessary but eases computation). Since employees collectively bargain with firms, wage and employment levels are decided from a bargaining game in which employees have some degree of bargaining power, denoted by $\phi_{it} \in [0,1]$. As shown in Dobbelaere & Mairesse (2013), the outcome of this bargaining is the generalized Nash-solution:

(C.4) $$\max_{w_{it}, L_{it}, M_{it}} (w_{it}L_{it} + (\bar{L}_{it} - L_{it})\bar{w}_{it})^{\phi_{it}}(R_{it} - w_{it}L_{it} - z_{it}M_{it})^{1-\phi_{it}}.$$

Maximization with respect to w_{it} and L_{it} gives:

(C.5) $$w_{it} = \bar{w}_{it} + \chi_{it}\left[\frac{R_{it} - w_{it}L_{it} - z_{it}M_{it}}{L_{it}}\right]$$

and

(C.6) $$w_{it} = MRPL_{it} + \phi_{it}\left[\frac{R_{it} - MRPL_{it}L_{it} - z_{it}M_{it}}{L_{it}}\right],$$

where $\chi_{it} = \frac{\phi_{it}}{1-\phi_{it}}$ denotes the relative extent of rent sharing. In this simple framework all the labor market power of the workforce is collected in ϕ_{it}. As equations (C.5) and (C.6) show, when employees possess positive bargaining power ($\phi_{it} > 0$), wages are above the

[83] In such a framework, employee-side labor market power can for instance result from employees exploiting long contract durations or institutional dismissal protections to spend below efficient effort levels.

marginal revenue product of labor. Note that equations (C.5) and (C.6) also nicely show that if firms can hire from a competitive pool of workers that do not coordinate their actions (i.e. a case where firms and workers do not bargain with each other), wages and marginal revenue products of labor will equalize. In that sense, the source of labor market power in the efficient bargaining model is the fact that firms are bound to hire workers from an organized community. This essentially constitutes a hiring friction (for more details please see McDonald & Solow (1981)).

Case 2: Employer-side labor market power – monopsonistic labor market

On a monopsonistic labor market firms set wages such that wages are below the marginal revenue product of labor. To do so, firms need to face a labor supply curve that is imperfectly elastic (Dobbelaere & Mairesse (2013)). Imperfectly elastic labor supply curves are typically motivated by labor market frictions that prevent workers from a costless switching between many firms. Among others, such frictions include imperfect information, local preferences, or moving costs (Boal & Ransom (1997); Burdett & Mortensen (1998); Bhaskar and To (1999); Dobbelaere & Mairesse (2013)). In the following, I derive an expression showing how imperfectly elastic labor supply curves translate into labor market power that allows firms to pay wages below marginal revenue products of labor.

Firms produce output using the production function (C.2). Now, firms do not bargain with a community of workers. Instead, firms unilaterally set wages. Consequently, the firm’s objective is to maximize the following version of equation (C.3):

(C.7) $$\max_{L_{it}, M_{it}} \Pi_{it}(w_{it}, z_{it}, L_{it}, M_{it}) = R_{it}(L_{it}, M_{it}) - w_{it}(L_{it})L_{it} - z_{it}M_{it}.$$

Maximization with respect to labor gives:

(C.8) $$MRPL_{it} = w_{it} + \frac{\partial w_{it}}{\partial L_{it}} L_{it} = w_{it}(1 + \frac{1}{\varepsilon_{it}^{L}}).$$

where $\varepsilon_{it}^{L} \geq 0$ denotes the labor supply elasticity. After reformulating equation (C.8), one receives:

(C.9) $$\frac{\varepsilon_{it}^{L}}{1 + \varepsilon_{it}^{L}} MRPL_{it} = w_{it}.$$

Equation (C.9) shows that only if firms face an imperfectly elastic labor supply, unilateral wage setting of a firm will lead to wages that are below the marginal revenue product of labor. In the absence of employee-side adjustment frictions that give firms' labor market power, we will have $\varepsilon_{it}^{L} = \infty$ and $w_{it} = MRPL_{it}$.

C.2 Deriving a parameter for labor market power

First, I derive equation (4.3) from the main text, which measures the degree of firms' output market power. The key assumption to derive (4.3) as a measure of output market power is that intermediate input markets are competitive, i.e. that unit costs for intermediates equal marginal revenue products of intermediate inputs (De Loecker & Warzynski (2012)). Using firms' production function (4.1), and the periodic cost function, $C(.) = r_{it}K_{it} + w_{it}L_{it} + z_{it}M_{it}$, where r_{it}, w_{it}, and z_{it} respectively denote the unit costs for capital (K_{it}), labor (L_{it}), and intermediates (M_{it}), we can formulate the following Lagrangian:

(C.10) $$\mathcal{L}_{it} = r_{it}K_{it} + w_{it}L_{it} + z_{it}M_{it} + \lambda_{it}\big(Q_{it} - Q_{it}(.)\big),$$

as intermediate input markets are competitive, the following first order condition holds:

(C.11) $$z_{it} = \lambda_{it}\frac{\partial Q_{it}}{\partial M_{it}}.$$

where $\lambda_{it} = \frac{P_{it}}{\mu_{it}}$, with P_{it} and μ_{it} being the firm's output price and the firm's price setting output market power (De Loecker & Warzynski (2012)). Latter also refers to the markup when all variable input markets are (equally) competitive.[84] Expanding (C.11) with $\frac{M_{it}}{Q_{it}}$ and reformulating leads to equation (4.3) of the main text:

(4.3) $$\mu_{it} = \theta_{it}^{M} * \frac{P_{it}Q_{it}}{z_{it}M_{it}}$$

where $\theta_{it}^{X} = \frac{\partial Q_{it}}{\partial X_{it}}\frac{X_{it}}{Q_{it}}$ denotes the output elasticity of input $X = \{L, M, K\}$.

[84] Obviously, it is up to the researcher to define which inputs are variable.

From equation (4.2) of the main text, i.e. from $(1+\tau_{it}^{L})=\frac{w_{it}}{MRPL_{it}}$, one can derive a similar expression. To see this, first use the assumption that intermediate input markets are competitive (which we also applied to derive (4.3) above). From that, we can expand (4.2) in the following way:

$$(1+\tau_{it}^{L})=\frac{w_{it}}{MRPL_{it}}\frac{MRPM_{it}}{z_{it}}=\frac{w_{it}}{MPL_{it}*MR_{it}}\frac{MPM_{it}*MR_{it}}{z_{it}}, \quad \text{(C.12)}$$

where $MRPM_{it}$, MR_{it}, MPL_{it}, and MPM_{it} respectively denote the marginal revenue product of intermediates, the marginal revenue, the marginal product of labor and the marginal product of intermediates. Rewriting (C.12) and expanding with $\left(\frac{\frac{M_{it}}{Q_{it}M_{it}}}{\frac{L_{it}}{Q_{it}L_{it}}}=1\right)$ gives:

$$(1+\tau_{it}^{L})=\frac{w_{it}}{z_{it}}\frac{\frac{\partial Q_{it}}{\partial M_{it}}\frac{M_{it}}{Q_{it}}}{\frac{\partial Q_{it}}{\partial L_{it}}\frac{L_{it}}{Q_{it}}}*\frac{L_{it}}{M_{it}}=\frac{w_{it}}{z_{it}}\frac{\theta_{it}^{M}}{\theta_{it}^{L}}\frac{L_{it}}{M_{it}}. \quad \text{(C.13)}$$

Expanding with $\frac{P_{it}Q_{it}}{P_{it}Q_{it}}$, substituting (4.3) into (C.13), and rearranging gives equation (4.4) of the main text:

$$\mu_{it}=\theta_{it}^{L}\frac{P_{it}Q_{it}}{w_{it}L_{it}}(1+\tau_{it}^{L}), \quad \text{(4.4)}$$

which is equivalent to:

$$\theta_{it}^{M}*\frac{P_{it}Q_{it}}{z_{it}M_{it}}=\theta_{it}^{L}\frac{P_{it}Q_{it}}{w_{it}L_{it}}(1+\tau_{it}^{L}). \quad \text{(C.14)}$$

Finally, rearranging yields equation (4.5) of the main text:

$$\gamma_{it}\equiv\frac{1}{(1+\tau_{it}^{L})}=\frac{\theta_{it}^{L}}{\theta_{it}^{M}}*\frac{z_{it}M_{it}}{w_{it}L_{it}}, \quad \text{(4.5)}$$

where γ_{it} denotes a measure of the firm's labor market power.

C.3 Firm characteristics and production function estimation results

TABLE C.1

SUMMARY STATISTICS FOR SAMPLE FIRMS

Variable	Mean (1)	Sd (2)	P25 (3)	Median (4)	P75 (5)	Observations (6)
Revenue labor share	0.31	0.12	0.22	0.30	0.39	177,957
Value-added share	0.77	0.24	0.64	0.76	0.88	177,957
Output elasticity of labor	0.28	0.10	0.21	0.28	0.35	177,957
Output elasticity intermediates	0.63	0.08	0.57	0.63	0.69	177,957
Output elasticity capital	0.11	0.06	0.07	0.10	0.14	177,957
Output market power parameter	1.09	0.14	1.00	1.07	1.16	177,957
Labor market power parameter	0.94	0.45	0.63	0.85	1.15	177,957
Deflated capital stock in thousands	26,400	124,000	2,370	6,492	19,600	177,957
Deflated intermediate input expenditures in thousands	25,500	118,000	2,446	6,293	19,000	177,957
Employees	220.11	621,41	47	91	209	177,957
Deflated capital per employee in thousands	95.72	95.56	38.16	68.56	119.41	177,957
Deflated intermediates per employee in thousands	87.23	66.99	41.79	68.06	110.92	177,957
Nominal value-added	14,200	59,500	1,981	4,367	11,600	177,957
Nominal revenue	41,500	18,600	4,760	11,300	32,200	177,957
Value-added over revenue	0.41	0.13	0.31	0.41	0.50	177,957
Average real wage	32,913	10,822	25,180	32,699	39,969	177,957
Log of real value-added per employee	16.32	1.39	15.26	16.16	17.22	177,957
Log of revenue weighted product market shares (euro-based)	0.96	1.91	-0.32	1.09	2.40	177,957
Log of firm price index	0.08	0.21	-0.01	0.06	0.19	177,957
Number of products	3.45	6.38	1	2	4	177,957
Export status dummy	0.76	0.43	1	1	1	177,957
Research & development dummy	0.26	0.44	0	0	1	177,957
Share of employment (sample firms)	0.000063	0.000172	0.000013	0.000026	0.000060	177,957
Share of revenue (sample firms)	0.000055	0.000240	0.000006	0.000015	0.000042	177,957
Import competition measure (firm-level)	1.47	4.98	0	0.02	0.53	177,957
Export opportunity measure (firm-level)	0.63	2.00	0	0.02	0.37	177,957

Notes: Table C.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.

TABLE C.2

PRODUCTION FUNCTION ESTIMATION:
MEDIAN OUTPUT ELASTICITIES, BY SECTOR

Sector	Number of observations (1)	Intermediate inputs (2)	Labor (3)	Capital (4)	Returns to scale (5)
15 Food products and beverages	25,447	0.65	0.17	0.13	0.94
17 Textiles	7,629	0.66	0.32	0.20	1.17
18 Apparel, dressing, and dyeing of fur	2,930	0.72	0.21	0.11	1.03
19 Leather and leather products	1,672	0.66	0.27	0.13	1.08
20 Wood and wood products	6,163	0.65	0.21	0.08	0.96
21 Pulp, paper, and paper products	6,033	0.68	0.25	0.07	1.00
22 Publishing and printing	5,352	0.57	0.22	0.06	0.84
24 Chemicals and chemical products	12,705	0.69	0.25	0.10	1.06
25 Rubber and plastic products	13,415	0.65	0.24	0.10	0.96
26 Other non-metallic mineral products	12,122	0.62	0.29	0.12	1.04
27 Basic metals	8,457	0.66	0.32	0.08	1.04
28 Fabricated metal products	27,506	0.59	0.30	0.10	0.98
29 Machinery and equipment	29,109	0.60	0.37	0.11	1.07
30 Electrical and optical equipment	1,417	0.63	0.27	0.22	1.12
31 Electrical machinery and apparatus	11,409	0.62	0.30	0.11	1.03
32 Radio, television, and communication	3,070	0.61	0.30	0.08	0.99
33 Medical and precision instruments	7,863	0.57	0.35	0.10	1.02
34 Motor vehicles and trailers	6,823	0.66	0.31	0.13	1.09
35 Transport equipment	2,853	0.60	0.31	0.07	0.95
36 Furniture manufacturing	10,172	0.63	0.32	0.17	1.11
Across all industries	202,147	0.63	0.28	0.10	1.01

Notes: Table C.2 reports median output elasticities calculated after estimating the production function (4.10) for every NACE rev. 1.1 two-digit industry with sufficient observations. Column 1 reports the number of observations used to calculate output elasticities for each industry. Columns 2-4 respectively report median output elasticities for intermediate, labor, and capital inputs. Column 5 reports median returns to scale. All regressions control for time dummies.

TABLE C.3

PRODUCTION FUNCTION ESTIMATION:
AVERAGE OUTPUT ELASTICITIES, BY SECTOR

Sector	Number of observations (1)	Intermediate inputs (2)	Labor (3)	Capital (4)	Returns to scale (5)
15 Food products and beverages	25,447	0.65	0.17	0.13	0.95
		(0.10)	(0.07)	(0.06)	(0.08)
17 Textiles	7,629	0.65	0.32	0.20	1.17
		(0.10)	(0.08)	(0.12)	(0.15)
18 Apparel, dressing, and dyeing of fur	2,930	0.72	0.22	0.12	1.05
		(0.12)	(0.12)	(0.05)	(0.09)
19 Leather and leather products	1,672	0.66	0.27	0.13	1.06
		(0.10)	(0.07)	(0.04)	(0.10)
20 Wood and wood products	6,163	0.65	0.22	0.08	0.95
		(0.09)	(0.12)	(0.04)	(0.09)
21 Pulp, paper, and paper products	6,033	0.68	0.24	0.07	1.00
		(0.09)	(0.10)	(0.04)	(0.08)
22 Publishing and printing	5,352	0.57	0.21	0.06	0.84
		(0.07)	(0.09)	(0.03)	(0.09)
24 Chemicals and chemical products	12,705	0.69	0.25	0.10	1.03
		(0.08)	(0.06)	(0.05)	(0.10)
25 Rubber and plastic products	13,415	0.65	0.24	0.10	0.99
		(0.07)	(0.08)	(0.05)	(0.10)
26 Other non-metallic mineral products	12,122	0.62	0.29	0.12	1.04
		(0.07)	(0.06)	(0.06)	(0.09)
27 Basic metals	8,457	0.66	0.31	0.08	1.06
		(0.09)	(0.09)	(0.05)	(0.10)
28 Fabricated metal products	27,506	0.59	0.30	0.10	0.99
		(0.08)	(0.10)	(0.03)	(0.09)
29 Machinery and equipment	29,109	0.60	0.38	0.11	1.09
		(0.08)	(0.10)	(0.04)	(0.13)
30 Electrical and optical equipment	1,417	0.64	0.28	0.22	1.14
		(0.09)	(0.07)	(0.08)	(0.08)
31 Electrical machinery and apparatus	11,409	0.62	0.30	0.13	1.05
		(0.06)	(0.09)	(0.07)	(0.15)
32 Radio, television, and communication	3,070	0.62	0.31	0.08	1.01
		(0.06)	(0.12)	(0.04)	(0.12)
33 Medical and precision instruments	7,863	0.57	0.34	0.10	1.01
		(0.05)	(0.06)	(0.02)	(0.11)
34 Motor vehicles and trailers	6,823	0.66	0.31	0.14	1.11
		(0.08)	(0.09)	(0.08)	(0.13)
35 Transport equipment	2,853	0.61	0.30	0.07	0.97
		(0.10)	(0.06)	(0.03)	(0.07)
36 Furniture manufacturing	10,172	0.63	0.31	0.17	1.12
		(0.09)	(0.11)	(0.10)	(0.16)
Across all industries	202,147	0.63	0.28	0.11	1.03
		(0.09)	(0.11)	(0.06)	(0.13)

Notes: Table C.3 reports average output elasticities calculated after estimating the production function (4.10) for every NACE rev. 1.1 two-digit industry with sufficient observations. Column 1 reports the number of observations used to calculate output elasticities for each industry. Columns 2-4 respectively report average output elasticities for intermediate, labor, and capital inputs. Column 5 reports average returns to scale. Associated standard deviations are reported in brackets. All regressions control for time dummies.

C.4 Identifying moments and estimating the production function by OLS

The identifying moments of the main text are formally given by:

(C.15) $$E\big((\varepsilon_{it} + \xi_{it})\mathbf{Y}_{it}\big) = 0,$$

with

(C.16) $$\mathbf{Y}'_{it} = (\,J_{it}(.),\ A_{it-1}(.),\ T_{it-1}(.),\ g_{it-1}(.),\ \mathbf{z}_{it-1}),$$

where for convenience I defined:

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

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

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

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

$\mathbf{z}_{it} = (exp_{it}, IMP_{it}^{CHN}, ProdCount_{it}, w_{it}).$

The notation follows the main text. exp_{it}, IMP_{it}^{CHN}, $ProdCount_{it}$, and w_{it} respectively denote a dummy variable for export status, firm-level import competition (as defined in section 4.5 of the main text), the number of products a firm produces, and the average wage it pays.

The Wooldridge-estimator used in the main text is based on an instrumental-variable-estimator where I instrument endogenous variables with their lags (see also Wooldridge (2009)). In my case, this refers to variables in $A_{it}(.)$ and $T_{it}(.)$. When estimating the production function by OLS (as below), I do not instrument those variables. In that case, $\mathbf{Y}'_{it}$ is given by:

(C.17) $$\mathbf{Y}'_{it} = (J_{it}(.),\ A_{it}(.),\ T_{it}(.),\ g_{it-1}(.),\ \mathbf{z}_{it-1}).$$

Table C.4 presents median output elasticities and returns to scale from estimating the production function of the main text by OLS. As in the main text, I estimated the production function separately for every NACE rev. 1.1 two-digit industry.

Table C.4

MEDIAN OUTPUT ELASTICITIES WHEN USING OLS, BY SECTOR

Sector	Number of observations (1)	Intermediate inputs (2)	Labor (3)	Capital (4)	Returns to scale (5)
15 Food products and beverages	25,447	0.65	0.16	0.13	0.95
17 Textiles	7,629	0.67	0.31	0.19	1.17
18 Apparel, dressing, and dyeing of fur	2,930	0.73	0.21	0.11	1.03
19 Leather and leather products	1,672	0.67	0.27	0.12	1.08
20 Wood and wood products	6,163	0.66	0.21	0.07	0.96
21 Pulp, paper, and paper products	6,033	0.68	0.25	0.07	1.01
22 Publishing and printing	5,352	0.57	0.22	0.06	0.84
24 Chemicals and chemical products	12,705	0.70	0.24	0.10	1.06
25 Rubber and plastic products	13,415	0.67	0.23	0.10	0.97
26 Other non-metallic mineral products	12,122	0.63	0.29	0.12	1.04
27 Basic metals	8,457	0.67	0.31	0.07	1.04
28 Fabricated metal products	27,506	0.60	0.30	0.09	0.99
29 Machinery and equipment	29,109	0.62	0.36	0.11	1.08
30 Electrical and optical equipment	1,417	0.63	0.30	0.22	1.17
31 Electrical machinery and apparatus	11,409	0.63	0.30	0.11	1.03
32 Radio, television, and communication	3,070	0.60	0.31	0.08	1.00
33 Medical and precision instruments	7,863	0.57	0.35	0.10	1.01
34 Motor vehicles and trailers	6,823	0.68	0.30	0.13	1.09
35 Transport equipment	2,853	0.61	0.30	0.06	0.96
36 Furniture manufacturing	10,172	0.65	0.31	0.16	1.10
Across all industries	202,147	0.64	0.28	0.10	1.02

Notes: Table C.4 reports median output elasticities calculated after estimating the production function (4.10) for every NACE rev. 1.1 two-digit industry with sufficient observations by OLS. Column 1 reports the number of observations used to calculate output elasticities for each industry. Columns 2-4 respectively report median output elasticities for intermediate, labor, and capital inputs. Column 5 reports median returns to scale. All regressions control for time dummies.

Note the close similarity between estimates reported in Tables C.4 and C.2. In fact, this implies that the endogeneity problem based on the dependence of firms' flexible input decision on the unobserved innovation in productivity is negligible in my case (after conditioning on all the variables in $B_{it}(.)$ and $g_{it-1}(.)$).

Table C.5 compares summary statistics for the variables of interest, one time derived from the baseline specification of the production function estimation, which I used in the main text, and one time from the specification where I estimated the production function by OLS. I report the former in Panel A and the latter in Panel B of Table C.5. Given the results from Table C.4, it is unsurprising that there are only minor differences between both.

TABLE C.5

SUMMARY STATISTICS FOR SAMPLE FIRMS,
BASELINE SPECIFICATION VS. OLS

Panel A: Baseline specification	Mean	Sd	P25	Median	P75	Observations
	(1)	(2)	(3)	(4)	(5)	(6)
Revenue labor share	0.31	0.12	0.22	0.30	0.39	177,957
Value-added share	0.77	0.24	0.64	0.76	0.88	177,957
Output elasticity of labor	0.28	0.10	0.21	0.28	0.35	177,957
Output market power parameter	1.09	0.14	1.00	1.07	1.16	177,957
Labor market power parameter	0.94	0.45	0.63	0.85	1.15	177,957

Panel B: OLS	Mean	Sd	P25	Median	P75	Observations
	(1)	(2)	(3)	(4)	(5)	(6)
Revenue labor share	0.31	0.13	0.22	0.30	0.39	177,874
Value-added share	0.77	0.24	0.64	0.76	0.88	177,874
Output elasticity of labor	0.28	0.10	0.21	0.28	0.35	177,874
Output market power parameter	1.11	0.14	1.01	1.09	1.18	177,874
Labor market power parameter	0.90	0.41	0.61	0.82	1.10	177,874

Notes: Table C.5 reports sample summary statistics for selected variables. Panel A reports statistics for the baseline specification of the main text, whereas Panel B reports statistics for the specification using an OLS-estimator to estimate the production function. Columns 1, 2, 3, 4, 5, and 6 respectively report the mean, standard deviation, 25th percentile, median, 75th percentile, and number of observations used to produce summary statistics for the respective variable.

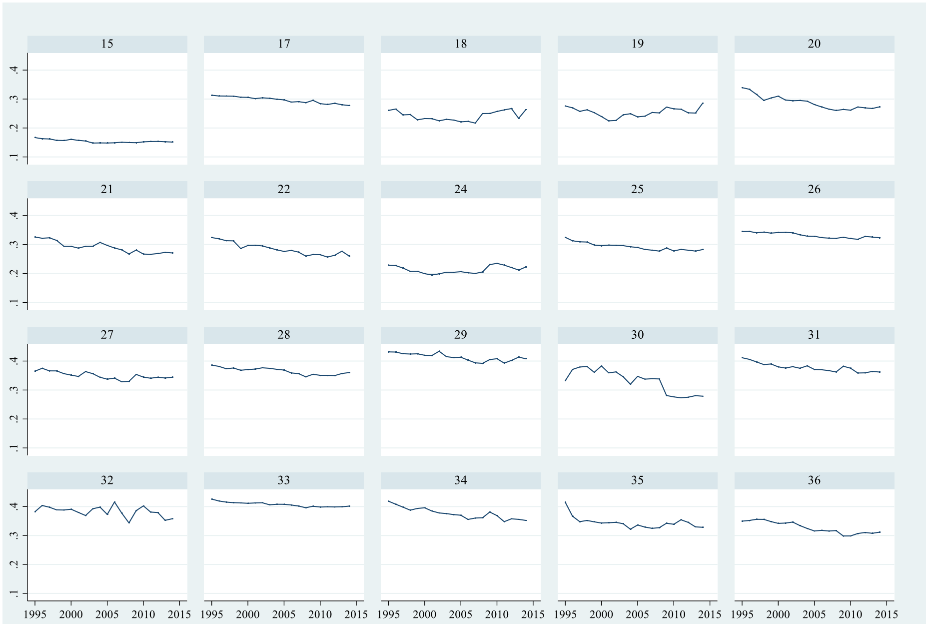
C.5 Two-digit industry-level changes of output elasticities

The main text shows the evolution of the aggregate output elasticity of labor and documents a clear time trend for this variable over a period of two decades. This raises doubts on the frequently applied assumption of constant output elasticities (as in many Cobb-Douglas production models) and implies a (potential) bias in estimates of total factor productivity, markups, or misallocation measures when deriving such measures from a framework featuring constant output elasticities of production factors. However, one argument in favor of the constant output elasticity assumption could be that output elasticities are constant at the sector level and that changes in aggregate output elasticities are driven by reallocation processes of economic activity between sectors. In that case, estimating a typical Cobb-Douglas production function for each industry separately would be valid.

To present evidence against this argument, Figures C.1, C.2, and C.3 respectively document the evolution of labor, capital, and intermediate input output elasticities at the two-digit sector level over the years 1995-2014. As can be immediately seen, labor output elasticities display a negative time trend across all 20 two-digit industries investigated in this study. With exception of industry 30 (electrical and optical equipment), changes in capital output elasticities (Figure C.2) are small. Thus, the assumption of constant output elasticities of capital at the two-digit industry level is approximately fulfilled for most two-digit industries in the German manufacturing sector for the period 1995-2014. In contrast, I find a clear positive trend for output elasticities of intermediates. This implies an increasing importance of intermediate inputs in the production activities of German manufacturing firms, which is consistent with an increasing tendency of German firms to offshore or outsource production activities (e.g. Sinn (2006); Wang, Wei, Yu, & Zhu (2016)).

The increased importance of intermediate inputs relative to labor and capital naturally implies a reallocation of revenue shares away from labor and capital towards intermediate inputs. This decreases the revenue wage share even in the presence of competitive factor and product markets. Note, however, that if the relative importance of capital and labor in firms' production activities, as well as firms' labor and product market power would stay constant, value-added labor shares would be unaffected from the relative increase in the importance of intermediate inputs. Yet, this is not the case. From the relative evolution of labor and capital output elasticities we know that the importance of capital in firms' production activities relative to labor has increased. Hence, even on counterfactually competitive markets, industry-level revenue labor shares would have decreased relative to capital shares. Equations (4.6) and (4.7) of the main text show that we can transfer this conclusion directly to the value-added based factor shares. This also suggests that the increase in the importance of intermediate inputs in firms' production processes is (mostly) associated with a substitution of labor for intermediate inputs. This is in line with the common notion that outsourced production activities are typically labor-intensive (e.g. Sinn (2006); Goldschmidt & Schmieder (2017)).

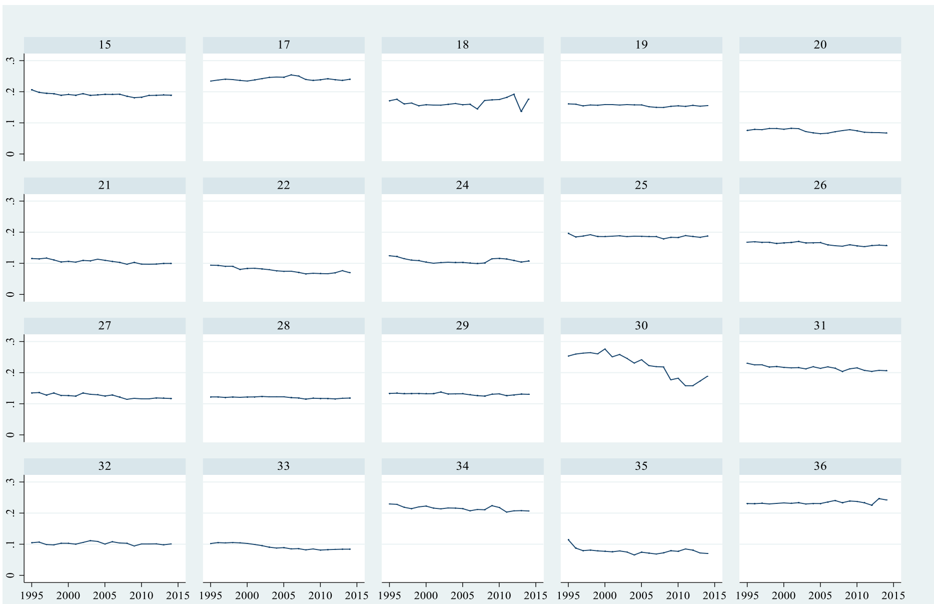
OUTPUT ELASTICITY OF LABOR, TWO-DIGIT SECTORS



Year

FIGURE C.1 – Industry-level output elasticities of labor, separately for two-digit industries. Sample firms.

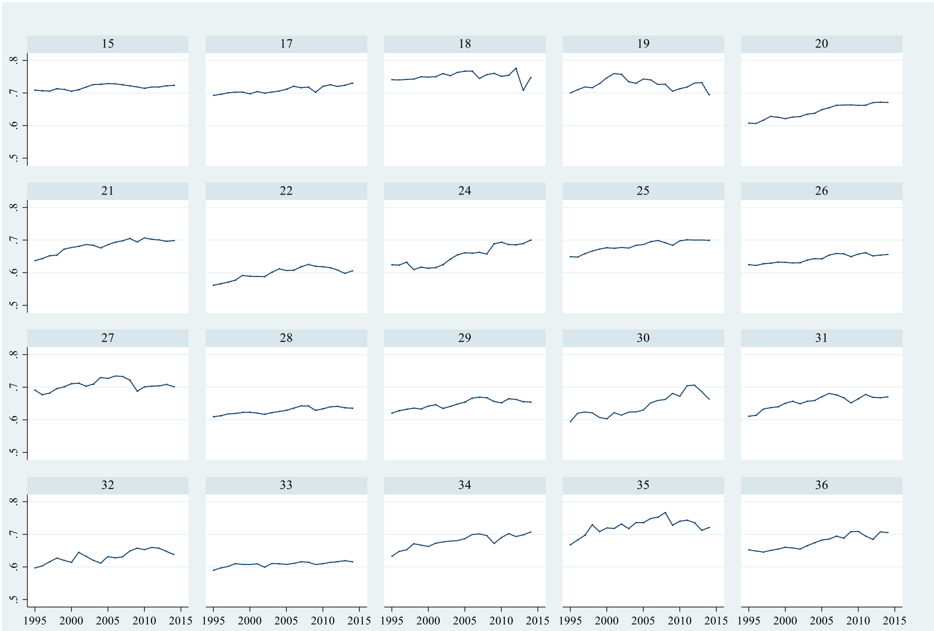
OUTPUT ELASTICITY OF CAPITAL, TWO-DIGIT SECTORS



Year

FIGURE C.2 – Industry-level output elasticities of capital, separately for two-digit industries. Sample firms.

OUTPUT ELASTICITY OF INTERMEDIATES, TWO-DIGIT SECTORS



Year

FIGURE C.3 – Industry-level output elasticities of intermediate inputs, separately for two-digit industries. Sample firms.

C.6 First stage regressions for IV-specifications

Table C.6 reports the first stage regression results for the IV-specification results documented in Table 4.3 of the main text. Note that the first stage is identical for all IV-regressions included in Table 4.3 of the main text. Therefore, Table C.6 reports only one regression for each endogenous variable. I denote the firm-level instrument variables for my import competition and export demand measures respectively by IMS_{it}^{INS} and EXS_{it}^{INS}.

TABLE C.6

FIRST STAGE REGRESSION RESULTS
FOR TABLE 4.3 OF THE MAIN TEXT

	IMP_{it-1}^{CHN} (1)	EXP_{it-1}^{CHN} (2)
IMS_{it-1}^{INS}	0.268***	0.0106***
	(0.0102)	(0.00186)
EXS_{it-1}^{INS}	-0.0523***	0.152***
	(0.00704)	(0.0108)
Firm x Industry FE	YES	YES
Time FE	YES	YES
Firm-level controls	YES	YES
Observations	114,060	114,060
R-squared	0.919	0.758
Number of firms	22,638	22,638

Notes: Table C.6 reports results from the first stage regressions when estimating equation (4.17) by IV. The dependent variable in column 1 is the lagged import competition measure, while in column 2 it is the lagged export opportunity measure. All regressions include time and industry times firm fixed effects and controls for lagged values of the firm's number of products, capital over labor ratio, and value-added over revenue ratio. Standard errors are clustered at the firm level. Significance: *10 percent, **5 percent, ***1 percent.

Table C.7 reports the first stage regression results for the IV-specification results documented in Table 4.5. In contrast to Table 4.3, Table 4.5 is based on two distinct samples. One is a sample of exporting firms, while the other is a sample of non-exporting.

TABLE C.7

FIRST STAGE REGRESSION RESULTS
FOR TABLE 4.5 OF THE MAIN TEXT

	Exporters		Non-Exporters	
	IMP_{it-1}^{CHN} (1)	EXP_{it-1}^{CHN} (2)	IMP_{it-1}^{CHN} (3)	EXP_{it-1}^{CHN} (4)
IMS_{it-1}^{INS}	0.273***	0.0102***	0.216***	0.00651
	(0.0112)	(0.00192)	(0.0271)	(0.00541)
EXS_{it-1}^{INS}	-0.0527***	0.156***	-0.0617	0.0951**
	(0.00630)	(0.0111)	(0.0391)	(0.0370)
Firm x Industry FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Firm-level controls	YES	YES	YES	YES
Observations	88,787	88,787	23,556	23,556
R-squared	0.922	0.755	0.908	0.805
Number of firms	17,066	17,066	6,068	6,068

Notes: Table C.7 reports results from the first stage regressions when estimating equation (4.17) separately for exporting and non-exporting firms by IV. The dependent variable in columns 1 and 3 is the lagged import competition measure, while in columns 2 and 4 it is the lagged export opportunity measure. All regressions include time and industry times firm fixed effects and controls for lagged values of the firm's number of products, capital over labor ratio, and value-added over revenue ratio. Standard errors are clustered at the firm level. Significance: *10 percent, **5 percent, ***1 percent.

C.7 Covariance between firms' employment share and variables of interest

COVARIANCE BETWEEN FIRM SIZE AND VARIABLES OF INTEREST,
USING EMPLOYMENT WEIGHTS

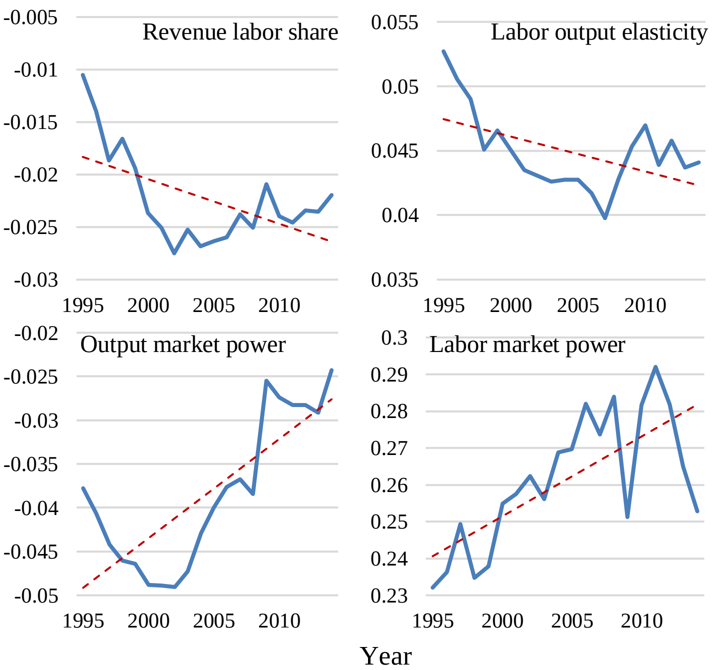


FIGURE C.4 – Covariance between firms' share in economic activity and firm-level labor shares, output elasticities of labor, output market power parameters, and labor market power parameters, when defining firms' share of economic activity as the employment share in total employment. Red dashed lines show trends. Germany's manufacturing sector. Sample firms.

Figure C.4 plots the between-firm term from the decomposition exercise of the main text, when defining firms' share of economic activity in terms of their share of employment in total employment (of sample firms). As can be seen, the general picture regarding the relationship between firm size and the variables of interest remains unchanged, i.e. larger firms in terms of employment are characterized by higher levels of labor market power, lower levels of product market power, higher output elasticities of labor, and smaller labor shares. Note that the time trends of the between-firm terms are also unaffected when using employment weights to define firms' share of economic activity.

C.8 Using constant product mix information to aggregate trade flows

One potential threat to my instrumental variable strategy is that firms might adjust their product mix in expectation of changing foreign import competition or export demand. In that case, weighting product-level trade flows with their importance to the firm before aggregating them introduces an endogeneity problem. To address this issue, I construct new instruments relying exclusively on firms' first observed product portfolio when weighting product-level trade flows. Using these new weights eliminates variation from endogenous product mix adjustments when estimating the effects of international trade on my outcomes of interest.

TABLE C.8

LABOR SHARES, MARKET POWER PARAMETERS, LABOR OUTPUT ELASTICITIES, AND INTERNATIONAL TRADE, USING INSTRUMENTS BASED ON FIRMS' FIRST PRODUCT PORTFOLIO

	IV			
	LS_{it} (1)	θ_{it}^{L} (2)	μ_{it} (3)	γ_{it} (4)
IMP_{it-1}^{CHN}	0.00250**	-0.00168*	-0.00020	-0.00463***
	(0.00100)	(0.000896)	(0.000338)	(0.00107)
EXP_{it-1}^{CHN}	-0.00565**	0.00329	0.00019	0.00756***
	(0.00287)	(0.00204)	(0.000949)	(0.00279)
Firm x Industry FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Firm-level controls	YES	YES	YES	YES
Observations	107,765	107,765	107,765	107,765
R-squared	0.914	0.951	0.899	0.937
First-stage F-test	75.17	75.17	75.17	75.17
Number of firms	21,289	21,289	21,289	21,289

Notes: Table C.8 reports results from estimating equation (4.17) by IV using newly constructed instruments based on firms' first observed product portfolio. The dependent variables in columns 1-4 respectively are the revenue labor share, the output elasticity of labor, the output market power parameter, and the labor market power parameter. All regressions include time and industry times firm fixed effects and controls for the firm's, capital over labor ratio, value-added over revenue ratio, and number of products. Standard errors are clustered at the firm level. Significance: *10 percent, **5 percent, ***1 percent.

Tables C.8 and C.9 report IV-results from estimating equation (4.17) using the newly constructed instruments. The structure follows the main text. I do not report OLS-results, however, as I apply the new weighting procedure exclusively to the instrumental variables. In comparison with the main text, one finds that results reported in Tables C.8 and C.9 are qualitatively similar to the baseline results. Yet, there are two effects that are statistically insignificant when using the baseline specifications, while becoming statistically significant at the 10-percent level when using the new instruments.

First, I find a negative effect of import competition on firms' output elasticity of labor when using the new instruments. However, given its imprecise estimation and its small value compared to the fall of the aggregate within-firm output elasticity of labor, one should interpret the coefficient on θ_{it}^{L} with caution.

Second, I find a positive effect of export demand from China on non-exporting firms' sales share in total sales of sample firms when using the new instruments. In Table 4.5 of the main text, one can see that the OLS-specification estimates a similar coefficient. Yet, as it is only statistically significant at the 10-percent level, one should not interpret too much into it. That being said, a plausible explanation for this positive effect is that some non-exporting firms enter the export market in response to growing foreign demand, leading to an increase in their sales share in total sales of sample firms.

TABLE C.9

INTERNATIONAL TRADE AND THE REALLOCATION OF ECONOMIC ACTIVITY, USING INSTRUMENTS BASED ON FIRMS' FIRST PRODUCT PORTFOLIO

	IV	
Panel A: Exporter	$\frac{L_{it}}{\sum L_{it}}$	$\frac{P_{it}Q_{it}}{\sum P_{it}Q_{it}}$
	(1)	(2)
IMP_{it-1}^{CHN}	-0.00937***	-0.0149***
	(0.00187)	(0.00228)
EXP_{it-1}^{CHN}	0.0177***	0.0281***
	(0.00455)	(0.00591)
Firm x Industry FE	YES	YES
Time FE	YES	YES
Firm-level controls	YES	YES
Observations	83,987	83,987
R-squared	0.982	0.981
First-stage F-test	65.98	65.98
Number of firms	16,065	16,065
	IV	
Panel B: Non-exporter	$\frac{L_{it}}{\sum L_{it}}$	$\frac{P_{it}Q_{it}}{\sum P_{it}Q_{it}}$
	(1)	(2)
IMP_{it-1}^{CHN}	-0.0186***	-0.0314***
	(0.00525)	(0.00757)
EXP_{it-1}^{CHN}	0.0211	0.0510*
	(0.0209)	(0.0287)
Firm x Industry FE	YES	YES
Time FE	YES	YES
Firm-level controls	YES	YES
Observations	22,165	22,165
R-squared	0.979	0.980
First-stage F-test	16.64	16.64
Number of firms	5.692	5.692

Notes: Table C.9 reports results from estimating equation (4.17) by IV using newly constructed instruments based on firms' first observed product portfolio. The dependent variable in columns 1 and 2 respectively is the firm-level employment share in total employment of sample firms and the firm-level sales share in total sales of sample firms. All regressions include time and industry times firm fixed effects and controls for the firm's number of products, capital over labor ratio, and value-added over revenue ratio. Standard errors are clustered at the firm level. Significance: *10 percent, **5 percent, ***1 percent.

C.9 Calculation of capital stocks

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

(C.18)
$$K_{it} = K_{it-1}\left(1 - \alpha_{jt-1}\right) + I_{it-1},$$

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

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

(C.19)
$$D_0 = \frac{1}{K_0}\sum\nolimits_0^\infty (\alpha K_t)t,$$

where the sum is taken over all periods t. αK_t denotes the amount of depreciated capital in period t. Assuming a linear capital depreciation, consistent with (C.18), implies: $K_t = K_0(1 - \delta_0)^t$. Substituting this into (C.19) and switching to continuous time gives:

(C.20)
$$D_0 = \frac{1}{K_0}\int_0^{\infty}(\alpha K_0(1-\alpha)^t)t\,dt.$$

After rearranging we have:

(C.21)
$$D_0 = \alpha\int_0^{\infty}(1-\alpha)^t t\,dt.$$

Using partial integration gives:

(C.22)
$$D_0 = \alpha\left[\frac{(1-\alpha)^t}{\ln(1-\alpha)}t\right]_0^{\infty} - \alpha\int_0^{\infty}\frac{(1-\alpha)^t}{\ln(1-\alpha)}dt.$$

Note that the first term on the right-hand side of (C.22) equals zero because $0 < \alpha < 1$. Integrating the remaining expression gives:

(C.23)
$$D_0 = \frac{\alpha}{\ln(1-\alpha) * \ln(1-\alpha)}.$$

Given that the expected lifetime, D_0, is known, (C.23) can be solved numerically.

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

(C.24)
$$\alpha_{jt} = \alpha_{jt}^{Build} \frac{K_{jt}^{Build}}{K_{jt}} + \alpha_{jt}^{Equip} \frac{K_{jt}^{Equip}}{K_{jt}},$$

where the superscript indicates whether the variable refers to a building or equipment specific variable. K_{jt}^{Build}, K_{jt}^{Equip}, and $K_{jt} = K_{jt}^{Build} + K_{jt}^{Equip}$ respectively denote the total building capital stock, the total equipment capital stock, and the total capital stock of an industry j in period t. Having calculated this depreciation rate, I use equation (C.18) to calculate firm-specific capital series.

To calculate the first capital stock of every capital series, I divide the reported tax depreciation (given in my data) by the depreciation rate. I do not use the tax depreciation variable in my law of motion because reported tax depreciations vary due to state induced tax incentives and, thus, do not necessary reflect the true amount of depreciated capital (e.g. House & Shapiro (2008)). Given that firms likely report too high values of depreciated capital due to such incentives, the first capital stock in each of my capital series is likely an overestimate of the true capital stock used in the firm's production activities. Yet, given that I estimate very reasonable output elasticities for capital (see Appendix C.3), I am confident that my capital variables reliably reflect firms' true capital stocks.[85]

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

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Chapter 5

Concluding Remarks

5.1 Conclusion

THIS DISSERTATION STUDIES how rising (import) competition and (export) demand, affect i) within-firm productivity, ii) firms' labor market power, and iii) labor's share in economic output. I address each of those three topics separately in one of three self-contained chapters. Although being structurally independent, each chapter provides novel causal empirical evidence that contributes to our understanding on how firms respond to changes in their product market conditions. While being derived from a trade setting, the findings of this dissertation are relevant also for the IO and labor market literature interested in understanding how product market shocks impact on firm performance and labor markets. All three studies have in common that they share the same database on German manufacturing sector firms, start from a production function framework to derive their results, and focus on a partial equilibrium analysis. Latter is important when discussing the policy relevance of my findings. In the following I provide such a discussion for each of the three chapters after briefly recapitulating each study's main findings.

Chapter 2 deals with a long-standing research question asking how (foreign) competition affects (domestic) firm productivity. The key finding is that only import competition from high-income countries causes a direct increase in within-firm productivity of German manufacturing sector firms. Competition from low-income countries leaves firm-productivity unaffected but encourages investment in R&D, which may result in long-run firm-productivity gains that are uncaptured by our empirical specification. The likely reason for this latter response is that German firms cannot directly compete with competitors from low-wage countries because, compared to those competitors, German wage-levels are relatively high. Instead, surviving German firms try to explore new markets and to invent new production technologies to escape competition from low cost producers. The chapter further provides evidence that the documented productivity gains from import competition from high-income countries may result from domestic firms exploiting their *existing but unutilized* potential to raise productivity. Consumers benefit from this increase in productivity by paying lower output prices.

If German manufacturing sector firms do not exhaust their full productivity potential in the absence of foreign competition, they must possess market power allowing them to produce below their maximum level of efficiency (Hicks (1935)). There is indeed compelling evidence that firms exhibit sizeable slack which explains a large part of the observed productivity dispersion between firms (Bloom, Genakos, Sadun, & Van Reenen (2012)). For instance, managers might consume a part of their firm's profits as leisure (Biggerstaff, Cicero, & Puckett (2016)). The results of this chapter suggest that such inefficiencies can be mitigated by policies encouraging competition with similar competitors.[86] Outside of a trade setting, policies that could promote this type of competition are product market (de)regulations, antitrust regulations, or policies encouraging firm entry. Yet, as we only focus on the partial equilibrium, we cannot draw conclusions on the general (welfare) gains and losses from trade or competition. We provide, however, evidence that efficiency gains, and likely also distributional impacts, from competition differ depending on the competitors' characteristics. This is important to know when designing industrial and trade policies and may also offer an

[86] Recap, if competition becomes too strong, we find that firms give up market shares and invest in R&D. For a theoretical framework explaining such differences in firms' responses to the intensity of competition please see Aghion, Bloom, Blundell, Griffith, & Howitt (2005).

additional explanation for why we observe trade agreements being first arranged between symmetric countries (Demidova (2008); Mertens (2017)).

Chapter 3 investigates how German manufacturing sector firms' labor market power is shaped by final product import competition and export opportunities from and to China. The chapter starts by documenting large heterogeneities in terms of labor market power across industries. While import competition decreases firms' labor market power, an increase in foreign demand raises firms' labor market power. When uncovering the mechanisms behind those effects, I find that firms in which employees possess labor market power cannot reduce labor expenditures sufficiently in response to adverse import competition shocks. This increases the labor market power of those firms' workers. On the other hand, firms' possessing themselves labor market power do not share export market gains with their workforce (i.e. they do not raise employment expenditures sufficiently) implying a further increase in those firms' labor market power from new export opportunities.

In sum, import competition and export demand therefore increase the absolute degree of labor market power distortions in Germany's manufacturing sector. As from an efficiency perspective firms having market power in their labor markets are too small and firms in which employees possess labor market power are too large, the increase in absolute labor market power distortions lowers aggregate output compared to a counterfactual scenario with perfect labor markets.[87] Thus, an increase in labor market power distortions from final product trade lowers aggregate trade gains compared to the predictions of widely applied standard models of trade with competitive labor markets.

The interactions between existing labor market distortions and changes in firms' product market conditions emphasize the complementary nature of labor market policies and

[87] For a model framework illustrating the underlying mechanism of such output losses please see Petrin & Sivadasan (2013) or Morlacco (2018).

industrial or trade policies. As also supported from structural models (as for instance in Dix-Carneiro (2014)), my findings suggest that the efficiency gains from product market competition (and thus final product trade) are hampered by inflexible labor markets on which employees possess labor market power (e.g. through long-term contracts). Although such labor market frictions might cushion adverse effects from (import) competition on workers, they also prevent efficiency gains from optimal firm adjustments. The findings of chapter 3 therefore support that from an efficiency perspective that aims at maximizing aggregate output, the market outcome could be improved by increasing the flexibility of labor inputs for firms that are adversely affected from (foreign) competition. This, of course, would increase the losses that individual workers in declining firms incur. To dampen these negative effects, efficiency gains could be redistributed to adversely affected workers.[88] Yet, assessing how to concretely design such a policy and whether such a policy would be desirable also from a welfare perspective is beyond the scope of this dissertation.

In contrast, firms having themselves labor market power and which experience profit gains from increasing (export) demand without sufficiently growing their labor expenditures stay too small from an efficiency perspective. In that case, it is more difficult to discuss appropriate policies dealing with this inefficiency. However, policies that increase firm competition in labor markets could generally proof beneficial to reduce such labor market power distortions. This is because promoting firm competition in labor markets would reduce the wage setting market power of firms, which would reduce the extent to which firms with labor market power artificially lower their labor demand and output. Yet again, from my partial equilibrium analysis I cannot infer on the effects of such policies on welfare and

[88] For instance, by supporting workers of declining firms to find new jobs or by providing financial support.

aggregate efficiency. Therefore, I leave a more in-depth discussion on the desirability of firm competition enhancing policies in labor markets open for future research.[89]

Notably, missing rent-sharing of export gains within firms possessing labor market power also offers a potential explanation for how globalization might has contributed to the fall in the aggregate labor share. Motivated by the findings of chapter 3, *chapter 4* investigates this further. The chapter starts by documenting a strong increase in firms' product and labor market power that coincides with the fall of the labor share in Germany's manufacturing sector. The increase in both types of market power account for 30% of the decline in Germany's manufacturing sector revenue labor share, which fell by 3.2 percentage points between 1995 and 2014. The remaining 70% are explained by a decreasing importance of labor in firms' production processes.

Increasing Chinese export demand contributes to the fall of the labor share by raising labor market power within firms and by inducing a reallocation of economic activity towards large exporting firms characterized by low labor shares, high productivity, and high labor market power. Latter points to a trade-off between aggregate gains in terms of productivity and a lower aggregate labor share resulting from trade induced reallocation processes. Product market (import) competition exerts slightly positive effects on the labor share by lowering firms' labor market power, which is consistent with evidence in chapter 3. Notably, changes in product market conditions do not lead to a reorganization of firms' production processes in a way that reduces the importance of labor to firms. This suggest that factors other than changes in international product market competition and demand are more important in

[89] In the review of chapter 4 below, however, I mention an example for such a policy in light of the observed joint distribution of size and labor market power in the German manufacturing sector.

explaining declining within-firm labor shares, which account for roughly half of the decline in the aggregate manufacturing sector labor share in Germany.[90]

Still, the documented increase in aggregate firm product and labor market power suggests room for policies that simultaneously increase aggregate output and labor's share of it. In chapter 4 I discuss that this holds especially for policies addressing firms' labor market power. However, whether such policies would be desirable depends on a variety of aspects including normative discussions on preferences. Covering this would go beyond the scope of this dissertation. If, however, policy makers decide to aim at a reduction of firms' labor market power, the design of an appropriate policy will depend on the underlying distribution of labor market power across firms. Given the documented covariance between firm size and labor market power, policies that affect all firms equally or small firms especially are unsuitable for reducing aggregate labor market power in the German manufacturing sector. Instead, to be effective, policies should target large firms. An example for such a policy is an extension of existing antitrust regulations, which currently mostly focus on an analysis of product market power, to also consider the effects of mergers on potential changes in firms' labor market power (Naidu, Posner, & Weyl (2018)).

5.2 Open research questions

Building on the findings of this dissertation, multiple roads for future research emerge. In the previous section I already highlighted the partial equilibrium nature of my analysis. Hence, an immediate implication for future research is to incorporate some of my findings into existing theoretical models. From that, one could for instance calculate the aggregate

[90] This may be associated with a rising importance of information and communication technologies or the offshoring of labor-intensive tasks to developing countries (e.g. Acemoglu (2003); Harrison (2005); Elsby Hobijn, & Şahin (2013); Karabarbounis & Neiman (2014); Caballero, Farhi, & Gourinchas (2017)).

welfare/efficiency loss from labor market power compared to product market power and assess the desirability of different policies addressing market power in both markets.[91]

In addition, there are several other research questions building on the findings of this dissertation. First of all, this dissertation focusses in all of its deliberations on the German manufacturing sector. A natural next step would therefore be to validate some of the findings of this dissertation also for other countries. Initiatives as The Competitiveness Research Network provide data for such cross-country analysis that could, among others, also shed light on the role of different institutions or regulations in explaining how changes in firms' product market conditions affects domestic firms, employees, and markets (The Competitiveness Research Network (2019)).

Although the manufacturing sector is ideal for studying the effects of (international) competition and demand shocks on firm-level outcomes, the economic importance of the service sector is large and growing (Loungani, Mishra, Papageorgiou, & Wang (2017)). Opening the analysis to other sectors to understand how changes in firms' product market environment affect productivity and labor market power outside of manufacturing would thus be highly interesting.

An important limitation of this dissertation is that firms' responses to changes in their product market conditions can only be documented for firms surviving the increase in competition (and, although not as critical, demand). This is because all associated econometric specifications rely on a time structure demanding firms to be present at least two consecutive years. Besides that, the data I use only contains information for firms with at least 20 employees. Therefore, I cannot investigate entry and exit decisions of firms, or how young vs. old firms perform in response to product market shocks. Although this is not crucial for

[91] See Berger, Herkenhoff, & Mongey (2019) for a recent example starting to explore this research direction.

the specific research questions I address, extending the analysis of this dissertation to analyze how competition and demand shocks affect young (small) firms that just entered the market compared to old (potentially large) firms would be a valuable project for future research. Notably, such an investigation could also contribute to the recent debate on the causes of rising market power and "superstar firms" (e.g. Autor, Dorn, Katz, Patterson, & Van Reenen (2018); De Loecker & Eeckhout (2018); De Loecker, Eeckhout, & Unger (2018)).

In addition, while I focus on the effects of final product import competition and export demand, extending the analysis of this dissertating to analyze how firm-specific intermediate input imports (i.e. competition in firms' supplier markets) shape firms' and their employees' labor market power would be an exciting research question. Due to data limitations one cannot pursue this topic further in the case of Germany. However, there are datasets allowing to address those question for other countries.[92]

Finally, I want to highlight that the key parameters for firm-productivity and firms' labor market power (but also for firms' product market power) are formally derived as residuals. To interpret those black-boxes, researchers have to impose a certain degree of structure. Throughout this dissertation, I try to minimize such defining assumptions and be agnostic about the forces shaping the derived residuals. For instance, due to having information on firms' output prices, I derive firms' productivity without imposing fixed markups or equal input prices across firms.

With respect to the market power parameters, however, it is generally hard to tell what kind of frictions they reflect. This makes it difficult to understand the underlying economic processes leading to product and labor market power. Ultimately, methods to derive product and labor market power parameters are based on comparing average marginal revenue

[92] See for instance Morlacco (2018) or Blaum, Lelarge, & Peters (2018) for French data.

products with average input costs at the firm level (see De Loecker & Warzynski (2012); Dobbelaere & Mairesse (2013)). Future work could further improve our understanding on what those wedges actually capture; for instance, in the case of the labor market power parameter by using detailed employer-employee datasets. A starting point could be to investigate which parameters drive variation in estimated differences between wages and marginal revenue products of labor across and within firms (e.g. skill composition, presence of worker councils, hiring and firing costs).[93] This could also improve our understanding on the channels through which changes in product market conditions affect labor markets. Additionally, from using linked employer-employee datasets, we could learn how labor market power of different worker groups evolves over time and how it changes in response to economic shocks. From that we could also learn more about the winners and losers from product market competition and demand shocks.

I hope that I can contribute to answering some of those open research questions in own future work.

[93] Similarly, Gorodnichenko, Revoltella, Svejnar, & Weiss (2018) recently investigated the role of a variety of firm-, sector-. and country-level characteristics in driving dispersion in marginal revenue products of capital and labor across firms.

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