IWH
Halle Institute for Economic Research
Member of the Leibniz Association

Discussion Papers

No. 18
October 2018

Labour Market Power and the Distorting Effects of International Trade

Matthias Mertens

Author

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

Editor

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

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

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

www.iwh-halle.de

ISSN 2194-2188

Labour Market Power and the Distorting Effects of International Trade*

Abstract

This article examines how trade shocks shape labour market imperfections that create market power in labour markets and prevent an efficient allocation of labour. I develop a framework for measuring such labour market distortions in monetary terms and document large degrees of those distortions in Germany's manufacturing sector. Import competition can only exert labour market disciplining effects when firms rather than workers have labour market power. Otherwise, export demand and import competition shocks tend to fortify existing distortions by amplifying labour market power structures. This diminishes the gains from trade compared to a model with perfectly competitive labour markets.

Keywords: international trade, market power, labour markets, allocative efficiency

JEL classification: D24, F14, F16, J50, L13, L60

* I thank Mareike Bauer, Eric Bartelsman, Richard Bräuer, Liuchun Deng, Sumit Deole, Sabien Dobbelaere, Marc Melitz, Steffen Müller, Georg Neuschäffer, Viktor Slavtchev, Ana Soares, Zhan Qu, Jo Van Biesebroeck, Juuso Vanhala, Yuan Zi, and seminar participants at the IWH, ifo Dresden, the annual CompNet conference 2018, and the annual INFER conference 2018 for insightful discussions and comments. I would particularly like to thank Michael Rößner, Christoph Schäfer, Denise Henker, and Alexander Giebler for their invaluable support on the data. I am grateful to Jan K. De Loecker, Pinelopi K. Goldberg, Amit K. Khandewal, Nina Pavcnik, Amil Petrin, and James Levinsohn for sharing their stata codes.

1. INTRODUCTION

WELFARE GAINS FROM GLOBAL INTEGRATION ARE NOT INCLUSIVE. Instead, trade creates winners and losers. While international trade is beneficial for 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.[1]

In principle, all those distributional effects can be rationalized in 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 and Kreickemeier 2009; Kambourov 2009; Dix-Carneiro 2014; Helpman, Itskhoki, Muendler, and Redding 2017). Imperfect labor markets not only imply distributional effects from trade, they also affect aggregate trade gains compared to a standard model with competitive labor markets. Therefore, understanding how labor market imperfections and international trade are linked with each other 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 trade shocks causally affect and interact 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 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 allocative inefficiencies that decrease aggregate output (Petrin and 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.[2] 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

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

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

employees, existing distortions might determine how firms adjust their labor expenses in response to trade shocks. However, how international trade influences labor market imperfections, to what extent prevalent labor market distortions determine distributional and allocative efficiency related 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 effects of trade shocks on firms' labor market power. This contributes to our understanding on how exactly international trade influences rent sharing between employees and their firms. Second, this study presents first empirical results on the causal effect of international trade on allocative inefficiencies emerging from imperfect labor markets. This offers insights on potential gains (losses) from trade in terms of allocative efficiency, a topic on which our knowledge is rather limited, so far.

My main results document that export demand shocks strengthen the labor market power of firms, whereas, oppositely, import competition shocks increase employees' labor market power. When uncovering the mechanisms behind those effects I find that existing structures of labor market power prevent a complete adjustments of firms' labor expenses to trade shocks. 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 beneficial export demand shocks. Complementarily, I find that firms facing a workforce with positive labor market power are not able to fully adjust to adverse import competition shocks 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, trade shocks 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 employed specification and only occur when firms rather than employees have labor market power.

In addition to the mentioned literature, this study contributes to the general literature on estimating the degree and impacts of labor market imperfections, which lately experienced an upswing in interest.[3] Recent academic work even suggests that welfare losses from labor market power might be larger than those

[3] E.g. Dobbelaere and Mairesse (2013); Petrin and Sivadasan (2013); Dobbelaere and Kiyota (forthcoming); Azar, Marinescu, Steinbaum, and Taska (2018); Marinescu and Hovenkamp (2018); Naidu, Posner, and Weyl (2018); Tortarolo and Zárate (2018).

from product market power and calls for antitrust remedies based on market power in labor markets (Marinescu and Hovenkamp 2018; Naidu et al. 2018). However, current measures of labor market distortions either lack an intuitive interpretation (Dobbelaere and Mairesse 2013) or rely on rarely available intermediate input price data to separately identify labor market from product market distortions (Petrin and Sivadasan 2013). I contribute to this strand of literature by combining the ideas of Dobbelaere and Mairesse (2013) and Petrin and Sivadasan (2013) to derive a monetary measure for labor market distortions that can easily be calculated with frequently available firm level data. The intuitive nature of this distortion measure allows an exact quantification of the monetary equivalent of labor market distortions, which reveals their staggering size: Median wages in the German manufacturing sector are 4,400 euro higher than perfect labor markets would imply.

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 import competition and export opportunities at the level of the firm. Measuring trade flows at the firm-product 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 different industries. In line with most of the recent trade literature, the analysis in this article focuses on trade shocks from China, whose unexpected and rapid rise to dominance in the global market offers an excellent playing field to study the impact from trade shocks on labor market outcomes (Autor, Dorn, and Hanson 2016). To draw causal inferences, I instrument my trade measures in the spirit of Autor et al. (2013) and Dauth, Findeisen, and Südekum (2014, 2016) 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, and Gautier (2016) find that export shocks increase the probability of signing firm level collective wage agreements. Moreover, for the UK, Hornstein, Krusell, and Violante (2005) document that there is some evidence that competitive pressure may lead to deunionisation. Most closely related to this paper, Boulhol, Dobbelaere, and Maioli (2011) find a negative impact of imports from developed countries on workers' bargaining power for the UK, while Nesta and 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 and 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 markets' allocative efficiency and international trade. Instead, it focuses on the distributional aspects. Second, research usually relies on measures of wage bargaining power that are difficult to interpret. However, ideally, we want to understand the quantitative dimension of labor market distortions, which is exactly the focus of my framework. Third, I do not restrict the causal analysis to import competition shocks. In fact, I find that labor market distortions react three to four times stronger to export demand shocks than to import competition shocks. Fourth, my results suggest that international trade interacts with existing structures of labor market distortions and tends to fortify prevalent labor market imperfections. This new finding implies that firms facing distinct types of labor market distortions do not react uniformly to trade shocks. Instead both, positive and negative gaps between marginal products and wages tend to widen in response to trade shocks, which is exactly the source of losses in terms of allocative efficiency from trade.

My study is also closely related to recent work that investigates how labor market frictions affect trade related labor market outcomes by estimating dynamic general equilibrium models (e.g. Artuç, Chaudhuri, and McLaren 2010; Dix-Carneiro 2014; Coşar, Guner, and 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, this study does not focus on general equilibrium outcomes 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 and to incorporate all kinds of labor market imperfections into the analysis. Moreover, my framework does not invoke any a priori assumptions on the relation between trade and labor market imperfections and takes into account 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, and Pavcnik (2016) find that Indian firms do not fully pass-through productivity gains from cheaper imported intermediate products to consumer prices, leading to an increase in markups. Arkolakis, Costinot, Donaldson, and Rodríguez-Clare (forthcoming) 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 can increase their markup relatively more, which reallocates production to the less efficient firms, giving rise to misallocation. In an empirical exercise Weinberger (2017) also shows evidence supporting his model implications.

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. In fact, 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 2 describes the data and explains the construction of trade shock measures. In chapter 3 I derive the framework for measuring labor market distortions in monetary terms. Chapter 4 presents the empirical results and Chapter 5 tests for their robustness. Chapter 6 concludes.

2. DATA DESCRIPTION AND CALCULATING TRADE SHOCKS

I use yearly data for the German manufacturing sector over the period 2000-2014 from the AFiD-database, supplied by the statistical offices of Germany. The data consists of two complementary parts. The first is a firm level panel for the years 2000-2014, containing, among others, data on expenditures, output, employment, investment, export activities and research and development activities, whereas the second part is a firm-product level panel for the period 1995-2014, supplying information on quantity and prices for every product a firm produces. As firms are obliged to answer, this data is of comparably high quality and contains only a negligible amount of missing values.[4] AFiD is limited to firms with more than 20 employees. To reduce the administrative burden, some variables in the firm level panel are only available for a representative subsample encompassing roughly 40% of firms with more than 20 employees. Among others, this contains expenditures on intermediate inputs or employment by full time equivalent (FTE). This subsample is stratified according to size class and industry, which are variables that I observe for all firms with more than 20 employees. Consequently, I can calculate inverse probability weights to translate

[4] 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.

my regression results to the full population of German manufacturing firms with more than 20 employees. Notably, the AFiD data also constitutes the basis for the national accounts data on Germany.

Bilateral trade flow data comes from the United Nations Comtrade Database (comtrade). The product dimension of AFiD allows me to merge the entire comtrade database at the firm-product level. From this combined dataset I can calculate trade flow measures at the disaggregated firm-product level by using information on the time specific product mix of a firm. Relying on firm-product rather than on industry level trade flow measures ensures that trade shocks vary between firms within industries, that I clearly identify final product trade shocks, and that multi-product firms, active in different industries, are taken into account.

In some cases, export values reported in comtrade exceed domestic production reported in AFiD. This could be because AFiD contains production information only for the population of manufacturing plants larger than 20 employees. Alternatively, there might be some reporting inconsistencies between comtrade and AFiD (e.g. due to differences in reporting days). To have well defined trade flow measures that are normalized between 0 and 100, I follow Mion and Zhu (2013) and define Chinese product level import competition, IM_{gt}^{CHN}, as the period t share of product g imports from China to Germany, $M_{gt}^{CHN\rightarrow GER}$, in the sum of Germany's total imports and total domestic production of product g, respectively denoted by M_{gt} and Y_{gt}:

$$(1) \qquad IM_{gt}^{CHN\rightarrow GER} = \frac{M_{gt}^{CHN\rightarrow GER}}{M_{gt} + Y_{gt}} * 100.$$

Complementary, I define export opportunities for German products, EX_{gt}^{CHN}, as:

$$(2) \qquad EX_{gt}^{GER\rightarrow CHN} = \frac{E_{gt}^{GER\rightarrow CHN}}{M_{gt} + Y_{gt}} * 100.$$

where $E_{gt}^{GER\rightarrow CHN}$ denotes product g exports from Germany to China. As I discuss in my empirical section, I follow existing work and 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}.

3. A FRAMEWORK TO ESTIMATE LABOR MARKET DISTORTIONS

This section describes the framework to estimate labor market distortions at the firm level. Section 3.1 starts by deriving a monetary quantifiable expression for labor market distortions. I discuss the interpretation of this parameter in section 3.2. Section 3.3 continues with a detailed treatment of the production function estimation needed to calculate firm specific labor market distortion parameters.

3.1 Deriving an expression for labor market distortions

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

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

where Q_{it} represents total physical output and L_{it}, M_{it}, and K_{it} respectively denote labor, intermediate, and capital inputs used in the production process. Firm specific total factor productivity is symbolized by ω_{it}. The only restriction on the functional form of $Q_{it}(.)$ 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, imperfections that drive wedges between marginal costs and marginal products of production inputs at the micro level signal allocative inefficiencies that reduce total output at the macro level (Petrin and Sivadasan 2013).[5]

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

[5] This follows from the fact that profit maximizing firms, active on perfect markets, would adjust their usage of input factors until marginal products equal marginal costs for every input. Deviations from this optimality condition indicate unutilized optimization potential compared to a neo-classical benchmark model. For a discussion see Petrin and Sivadasan (2013).

(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 allocative efficient case ($V_{it}^{L} = MRPL_{it}$). 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 applied in Tortarolo and Zárate (2018) and in Lu, Sugita, and Zhu (2018), to which I refer for further discussions. However, as labor market distortions are an outcome of a variety of different 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 revenue products of labor (e.g. Hsieh and Klenow 2009; Petrin and Sivadasan 2013; Dobbelaere and Mairesse 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 allow $f_{it}(\boldsymbol{S}_{it})$ to have a general functional form, i.e. I abstain from restricting $f_{it}(\boldsymbol{S}_{it})$ to reflect 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 and 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 and Taylor (1991), or as a result of hiring and firing costs, as in Petrin and Sivadasan (2013).

The problem in using equation (4) is to recover a consistent measure of $MRPL_{it}$. To circumvent this problem, I follow Dobbelaere and Mairesse (2013) in using the intermediate input market as a competitive benchmark to express δ_{it}^{L} as a function of measurable variables. In the online appendix B, I show that this translates into:

$$(5) \qquad \delta_{it}^{L} = V_{it}^{L} - \frac{V_{it}^{M}}{MPM_{it}} MPL_{it} = \frac{V_{it}^{L} L_{it}}{L_{it}} - \frac{\theta_{it}^{L}}{\theta_{it}^{M}} * \frac{V_{it}^{M} M_{it}}{L_{it}},$$

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

Assuming competitive intermediate input markets to identify labor market distortions might seem restrictive. However, throughout the literature on estimating markups and production functions by control function approaches, exactly this assumption is key in ensuring identification. Using it to derive a measure of labor market distortions is therefore fully consistent with the existing literature. Still, I address potential concerns about biases introduced by non-competitive intermediate input markets when estimating the impact of trade shocks on δ_{it}^{L}.

Interestingly, equation (5) can be linked to the current workhorse framework of Dobbelaere and 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. To see the similarity between the framework of Dobbelaere and Mairesse (2013) and the approach in this article, note that equation (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 and Mairesse (2013) implies the value of δ_{it}^{L}.[6] However, the advantage of the approach in this study is i.) that I abstain from assuming perfect flexibility of labor inputs and ii.) that I express labor market distortions in monetary terms, which enables intuitive interpretations of labor markets imperfections. In fact, the monetary nature of δ_{it}^{L} is exactly what allows me to present evidence that models assuming that labor market distortions are solely driven by wage setting power, subsequent to a perfectly flexible labor input decision (as e.g. in Dobbelaere and Mairesse 2013), are inconsistent with my and existing results in the literature.[7]

---

[6] For the derivation see the online appendix B. Since the key assumption for identifying δ_{it}^{L} is that firms' intermediate input markets are competitive, I show in the online appendix C that μ_{it}^{M} displays a clearly larger dispersion than μ_{it}^{L} across firms. This is consistent with the idea that intermediate input markets are more competitive than labor markets and that cross-sectional variation in μ_{it}^{L} is driven by variation in labor market distortions.

[7] Equation (5) is similar to the allocative inefficiency measure in Petrin and Sivadasan (2013). The difference is that equation (5) is scaled by the wedge between marginal revenue products and costs for intermediate inputs. This allows to identify labor market distortions separately from product market imperfections.

3.2 Labor market power, allocative inefficiencies, and adjustment frictions

In equation (5), 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 $\delta_{it}^{L} < 0$). As discussed below, I will interpret δ_{it}^{L} as an inverse measure of firms' labor market power, i.e. negative values of δ_{it}^{L} signal labor market power of firms, whereas positive values of δ_{it}^{L} indicate positive labor market power for the firm's workforce. Defining δ_{it}^{L} as a measure of labor market power follows Dobbelaere and Mairesse (2013), who motivate deviations from $\delta_{it}^{L} = 0$ by the presence of wage bargaining power. However, since observing $\delta_{it}^{L} \neq 0$ can also result from adjustment frictions, I prefer the more general wording. In fact, adjustment barriers are a natural source of market power in labor markets and the existence of labor market power is often motivated by some sort of adjustment friction (e.g. Manning 2003; Naidu, et al. 2018).

To fix ideas on the definition of labor market power and its relation to adjustment frictions, think of how workers can exploit inflexible contracts to spend only low effort levels, such that their compensation is above their output contribution (similar to a labor hoarding model). In that case, the market power of employees is not reflected in a wage bargaining power, it is power over firms' labor quantity and wage adjustments. Similarly, frictions like moving costs of employees that can be exploited by firms are a typical argument for the existence of monopsonistic labor markets (Manning 2003). Strictly speaking, also efficient bargaining models, where firms and unions bargain with each other, model some sort of 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 and Solow 1981).

However, given the limited information on industrial relations and workforce compositions in my data, I cannot investigate into the exact sources of δ_{it}^{L}. In principle, this makes a clear distinction between intentional exploitation of labor market power or unintentional adjustment frictions difficult. Nevertheless, in my empirical analysis I show that firms with ($\delta_{it}^{L} < 0$) and without ($\delta_{it}^{L} > 0$) labor market power differ in their reactions trade shocks. This implies that physical/technical adjustment barriers faced by all firms equally are unlikely to have a significant role in driving the reactions of δ_{it}^{L}. Moreover, I show that firms with labor market power are larger, more capital intensive, and more productive. Those facts fit very intuitively into a story where large "superstar" firms exert market power in concentrated labor markets, which is in line with recently documented empirical evidence (e.g. Autor, Dorn, Katz, Patterson, and Van Reenen 2017; Azar et al. 2018).

In contrast to δ_{it}^{L}, which reflects the distribution of rents between firms and employees, absolute values of δ_{it}^{L} abstract from distributional aspects and measure firms' contribution to the total extent of (allocative) labor market inefficiencies (compared to a socially optimal neo-classical benchmark scenario). This follows from the fact that perfect labor markets would eliminate every positive and negative gap between wages and MRPL. Petrin and Sivadasan (2013) illustrate this within a simple accounting framework and show that larger 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 $|\delta_{it}^{L}|$ as a measure of the firm's contribution to allocative labor market inefficiencies follows the work of Petrin and Sivadasan (2013) and uses their definition of allocative inefficiency. Note, however, that this also nicely links into the above definition of labor market power, since, 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 $\delta_{it}^{L} < 0$. Notably, as $|\delta_{it}^{L}|$ abstracts from product market imperfections, using $|\delta_{it}^{L}|$ as a measure of labor market (in)efficiency is consistent with allowing for a certain degree of product market power to be beneficial (e.g. as innovation or entry incentive).

Before using equation (5) and regressing trade shocks on δ_{it}^{L} and $|\delta_{it}^{L}|$, one first needs 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. However, since I observe firm-product level prices, I can account for firm specific price variation. Although theoretically important, correcting for firm level price variation only marginally affects responses of labor market distortions to trade shocks in my case. However, as I show in the online appendix D, ignoring firm price variation increases *levels* of labor market distortions, leading to a higher share of firms and industries in which employees possess labor market power.

3.3 Production function estimation

I use a translog specification because it allows for *time varying and firm specific* output elasticities. For estimation, I use firm level intermediate input, capital stock, FTE, and total output for M_{it}, K_{it}, L_{it}, and Q_{it}, respectively.[8] The production function is given by:

$$q_{it} = \boldsymbol{\phi}'_{it}\boldsymbol{\beta} + \omega_{it} + \varepsilon_{it}, \tag{6}$$

where lower-case letters denote 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.[9] Time varying 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.[10] Due to the dependence of firms' intermediate inputs on ω_{it}, estimation of equation (6) by OLS is inconsistent. Besides this simultaneity problem, firm specific prices are usually unobserved. Hence, estimating equation (6) without controlling for firm level price variation, will bias the input coefficients if input prices are correlated with input choices.

3.3.1 Unobserved output and input prices

To deal with unobserved output prices I follow Eslava, Haltiwanger, Kugler, and Kugler (2004) in calculating a firm specific price index by relying on product level price information given in my data. I purge observed firm revenue 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 Berry (1994) and De Loecker et al. (2016) who have shown that for general models of demand, market shares and product dummies can 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:

[8] The calculation of capital stocks follows Bräuer, Mertens, and Slavtchev (2018) 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.

[9] 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: $\frac{\partial q_{it}}{\partial l_{it}} = \beta_l + 2\beta_{ll} l_{it} + \beta_{lm} m_{it} + \beta_{lk} k_{it} + \beta_{lkm} k_{it} m_{it}$.

[10] The assumption of quasi-fixed labor inputs is also employed in several other studies (e.g. in De Loecker et al. 2016 for India, Valmari 2016 for Finland, and Ackerberg and Hahn 2015 for Chile). Due to the high degree of employment protection in Germany (OECD 2013), it seems especially justified to treat labor as a quasi-fixed input in my case.

$$B_{it}(.) \equiv B_{it}\big((\pi_{it}, \boldsymbol{ms}_{it}, G_{it}, D_{it}) \times \boldsymbol{\phi}_{it}^{c}; \boldsymbol{\beta}\big). \tag{7}$$

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 firm 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 the fact 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 price variation to be present with respect to all elements in $B_{it}(.)$. 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.

3.3.2 Unobserved productivity and identifying moments

To avoid 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 and Pakes (1996) and Levinsohn and 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:

$$\omega_{it} \equiv g_{it}(.) = g_{it}(e_{it}, k_{it}, l_{it}, \boldsymbol{z}_{it}), \tag{8}$$

where, in addition to k_{it} and l_{it}, $\boldsymbol{z}_{it}$ captures other state variables of the firm. Capital and labor enter the state variable space because of their dynamic implications arising from adjustment costs. 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 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 helps absorbing unobserved quality and input price differences that shift demand for e_{it} (De Loecker and Scott 2016). Assuming that Hicks-neutral 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 (7) and (8) into (6) leads to:

$$q_{it} = \widetilde{\boldsymbol{\phi}}_{it}'\boldsymbol{\beta} + B_{it}(.) + g_{it-1}(.) + \varepsilon_{it} + \xi_{it}, \tag{9}$$

which constitutes the basis of my estimation.[11] I estimate (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 $\varepsilon_{it} + \xi_{it}$:

$$E\big((\varepsilon_{it} + \xi_{it})\boldsymbol{\Upsilon}_{it}\big) = 0, \tag{10}$$

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 markets shares and 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 as well as 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

4. EMPIRICAL RESULTS

This chapter presents the empirical results. Section 4.1 discusses descriptive evidence on the degree of labor market distortions within the German manufacturing sector. Section 4.2 presents the main findings of this article,

[11] 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).

documenting how trade shocks affect labor market distortions. Section 4.3 continues by shedding light on the mechanisms underlying those results.

4.1 Labor market distortions in the German manufacturing sector

Table 1 presents median output elasticities for capital, labor, and intermediate inputs from estimating the production function (9) separately for every NACE rev. 1.1 two-digit industry with sufficient observations. Column 1 reports the number of firm-year observations used to calculate output elasticities and returns to scale. Columns 2-5 respectively report median output elasticities for intermediate, labor, and capital inputs as well as median returns to scale. 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. 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.

TABLE 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	24,013	0.63	0.10	0.16	0.89
17 Textiles	5,908	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	1,327	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	4,746	0.46	0.15	0.38	1.09
24 Chemicals and chemical products	11,632	0.71	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	9,567	0.66	0.32	0.10	1.09
27 Basic metals	7,112	0.68	0.31	0.05	1.02
28 Fabricated metal products	23,866	0.59	0.31	0.12	0.99
29 Machinery and equipment	28,216	0.61	0.37	0.08	1.05
30 Electrical and optical equipment	1,432	0.58	0.32	0.07	0.93
31 Electrical machinery and apparatus	10,401	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	7,890	0.59	0.27	0.19	1.07
34 Motor vehicles and trailers	6,709	0.68	0.31	0.26	1.27
35 Transport equipment	2,939	0.64	0.31	0.09	1.09
36 Furniture manufacturing	8,001	0.65	0.28	0.05	0.96
Across all industries	180,317	0.63	0.28	0.10	1.01

Notes: Table 1 reports median output elasticities from estimating the production function (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.

From the estimated output elasticities, I calculate labor market distortion parameters by using equation (5). Table 2 documents industry specific sample median values for δ_{it}^{L}, its absolute value, average yearly person wages, and the difference between markups based on firms' intermediate and labor input decision.[12] The latter difference is included as it implies the value of δ_{it}^{L} and is frequently used as a measure of labor market distortions in the literature (e.g. Dobbelaere and Mairesse 2013 and subsequent work). Across all industries, given firms' number of employees, the median firm pays its workers a wage that is 4,400 euros above the wage that perfect labor markets would imply (column 1). Relating this figure to observed wages, one finds that median distortions equal to $\frac{4{,}371.89*100}{36{,}521.04} \approx 12\%$ of paid wages. Moreover, labor market distortions are reflected in median wages ranging from 13,500 euro *above* (medical and precision instruments) to 6,800 euro *below* (pulp, paper, and paper products) the wage that, given firms' employment and flexible input decision, would realize the competitive labor market outcome. Intuitively, one would expect that industries characterized by high wages and which manufacture technologically sophisticated products would feature a strong workforce. Whereas this intuition holds for several industries (e.g. medical and precision instruments), above median values of δ_{it}^{L} are not always associated with above median 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 likely results from frictions that protect unproductive workers from being dismissed (e.g. hiring and firing costs or long-term contracts). Notably, I find clearly higher median values of δ_{it}^{L} for West-German (5,400 euros) compared to East-German firms (390 euros), which is consistent with the common perception that West-German employees possess higher levels of labor market power.

Column 2 shows the degree of absolute labor market distortions, which abstracts from distributional outcomes and solely measures the total extent of labor market inefficiencies. Whereas the publishing and printing industry displays 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 6,700 euros *per full-time worker*.

---

[12] For more details on the sample firms' characteristics see the online appendix A. 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 (results are available on request). Labor market distortions as measured by equation (5) are independent of this error correction.

TABLE 2

SAMPLE MEDIANS FOR LABOR MARKET DISTORTIONS, FIRM WAGES, AND MARKUPS, 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 (6)
15 Food products and beverages	12,506.28	12,516.81	24,463.46	0.50	17,977
17 Textiles	8.84	8,849.06	31,651.93	0.00	5,772
18 Apparel, dressing, and dyeing of fur	4,763.23	8,819.77	29,988.74	0.19	1,766
19 Leather and leather products	8,910.00	9,740.76	27,000.33	0.38	936
20 Wood and wood products	1,411.28	6,745.56	31,496.06	0.05	4,741
21 Pulp, paper, and paper products	-6,827.43	12,517.63	38,609.97	-0.20	4,107
22 Publishing and printing	-6,746.72	21,638.76	37,519.39	-0.14	1,475
24 Chemicals and chemical products	-1,943.86	11,461.76	46,002.97	-0.05	11,483
25 Rubber and plastic products	5,569.34	6,780.32	34,616.85	0.17	11,214
26 Other non-metallic mineral products	-2,881.98	9,698.15	36,840.14	-0.09	8,947
27 Basic metals	-4,021.13	12,418.3	40,972.91	-0.11	5,898
28 Fabricated metal products	5,395.74	11,015.09	36,130.12	0.18	23,672
29 Machinery and equipment	1,722.88	12,593.54	42,261.64	0.05	27,790
30 Electrical and optical equipment	-146.56	17,318.68	41,148.26	0.00	804
31 Electrical machinery and apparatus	1,351.52	12,736.70	37,315.81	0.04	10,131
32 Radio, television, and communication	3,872.30	16,182.19	35,551.46	0.13	2,387
33 Medical and precision instruments	13,465.69	16,826.59	38,140.48	0.47	7,506
34 Motor vehicles and trailers	-1,011.10	20,231.55	37,436.22	-0.03	5,391
35 Transport equipment	6,278.08	17,099.38	38,518.78	0.19	2,005
36 Furniture manufacturing	6,410.18	7,701.79	30,343.83	0.24	5,723
Across all industries	4,371.89	11,434.63	36,521.04	0.14	159,725

Notes: Table 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 markups based on firms' intermediate and labor input decision in the associated industry. 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 markup differences I estimate, and which imply the euro value of distortions, are smaller than documented in the literature.[13] Consequently, the monetary labor market distortions reported in Table 2 are also *small* compared to implied estimates in the existing literature. 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 many different frictions, including wage bargaining power but also adjustment barriers to labor. Under this view, a reduction of labor market

[13] Existing studies document industry level markup differences ranging from -0.69 to 0.91, from -0.29 to 0.76, and from -2.57 to 0.91 respectively for France, Japan, and The Netherlands (Dobbelaere, Kiyota, and Mairesse 2015), from -2.25 to 1.93 and from -0.23 to 1.05 respectively for Chile and France (Dobbelaere et al. 2016) and from -1.10 to 0.50 for France (Dobbelaere and Mairesse 2013).

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.

TABLE 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	96.53	3.47	18,468
17 Textiles	50.09	49.91	5,778
18 Apparel, dressing, and dyeing of fur	69.16	30.84	1,767
19 Leather and leather products	80.02	19.98	936
20 Wood and wood products	55.49	44.51	4,759
21 Pulp, paper, and paper products	33.55	66.45	4,217
22 Publishing and printing	40.34	59.66	1,688
24 Chemicals and chemical products	45.38	54.62	11,581
25 Rubber and plastic products	76.48	23.52	11,279
26 Other non-metallic mineral products	42.31	57.69	8,963
27 Basic metals	40.95	59.05	5,963
28 Fabricated metal products	64.97	35.03	23,803
29 Machinery and equipment	53.62	46.38	28,202
30 Electrical and optical equipment	47.52	52.48	909
31 Electrical machinery and apparatus	52.88	47.12	10,265
32 Radio, television, and communication	55.70	44.30	2,684
33 Medical and precision instruments	78.08	21.92	7,760
34 Motor vehicles and trailers	44.36	55.64	6,095
35 Transport equipment	58.43	41.57	2,100
36 Furniture manufacturing	76.86	23.14	5,766
Across all industries	61.30	38.70	162,983

Notes: Table 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.

Labor market power determines how firms share profits with their workforce. Therefore, labor market power structures should be relevant for determining how firms pass-through trade related profit changes into wage and employment adjustments. To investigate the extent to which trade shocks and prevalent labor market distortions interact with each other, I run separate regressions for firms with positive and negative values of δ_{it}^{L} when estimating the effects of trade shocks on labor market distortions. This separation of firms follows existing work which classifies firms with $\delta_{it}^{L} > 0$ into efficient-bargaining and firms with $\delta_{it}^{L} < 0$ into monopsonistic regimes. Using this classification scheme, Table 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 hosts 96.5 percent PD-firms), 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, 61.3 (38.7) percent of my firm-year observations can be classified as PD-firms (ND-firms).[14] Notably, at the firm level, switching between both categories occurs only in 7.7% of all cases, i.e. within firms, the classification into PD- and ND-firms is stable across time.

To get an impression on the characteristics of PD- and ND-firms, I estimate the following equation by OLS:

$$\ln y_{it} = \gamma_0 + \gamma_i PD_{it} + \upsilon_j + \upsilon_t, \tag{11}$$

where PD_{it} is a dummy for being a PD-firm. υ_j and υ_t capture industry j and time fixed effects and y_{it} can be any variable of interest. Table 4 shows results from estimating (11) using the logs of wages, FTE, produced output, markups, capital per labor ratios, and value added per FTE as dependent variables. Those variables give an intuition about the performance, size and, wage differences between PD- and ND-firms, which may be relevant in explaining labor market power structures. I stress that Table 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, charge higher markups, display a lower labor productivity, and have lower capital to labor ratios.

[14] Often, classification is based on statistical tests, which, however, involves normative and arbitrary decisions on when to classify a distortion as being compatible with perfect competition (e.g. Dobbelaere and Mairesse 2013). Therefore, I abstain from using statistical tests for my classification. Still, 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 is 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 4

Differences between PD- and ND-Firms	Wages (1)	FTE (2)	Output (3)	Markups (4)	Capital per FTE (5)	Value added per FTE (6)
PD_{it}	0.0568*** (0.00465)	-0.964*** (0.0144)	-1.289*** (0.0188)	0.170*** (0.00302)	-0.470*** (0.0117)	-0.0563*** (0.00948)
Industry FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
Observations	146.240	146.240	146.240	146.240	146.240	146.240
R-squared	0.274	0.239	0.274	0.265	0.161	0.061
Number of firms	31,934	31,934	31,934	31,934	31,934	31,934

Notes: Table 4 reports results from estimating equation (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 charge higher markups and pay higher wages at the same time. Interestingly, although PD-firms constitute the larger share of firms across most industries, ND-firms employ more workers. Consequently, the share of workers employed in firms with labor market power is higher than suggested from industry level evidence.

4.2 Trade shocks and labor market distortions

The most intuitive way how international competition can affect labor market distortions is by affecting labor demand (e.g. Rodrik 1997; Hasan, Mitra, and Ramaswamy 2007). Among others, such effects can be realized by trade induced adjustments in the organizational structure and product mix of firms (e.g. Caliendo and Rossi-Hansberg 2012; Mayer et al. 2014). The approach I follow is, however, consistent with any channel, as I do not invoke any a priori assumptions on the mechanisms through which trade interacts with labor markets.

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

$$y_{it} = \gamma_{IMP} IMP_{it-1}^{CHN} + \gamma_{EXP} EXP_{it-1}^{CHN} + \boldsymbol{C}_{it-1}' \boldsymbol{\gamma} + \upsilon_{i*j} + \upsilon_t \,, \tag{12}$$

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, which are lagged to avoid over-controlling.[15] υ_t and υ_{i*j} respectively capture time and firm times industry fixed effects, whereas y_{it} can symbolize any variable of interest. Estimating the model in levels while controlling for firm fixed effects uses the same identifying variation as a first difference model (i.e. effects are identified through within firm changes in the explanatory variables). However, as I use an unbalanced panel of firms, a fixed effects estimator avoids a disproportional loss of observations when identifying within firm effects.

Table 5 displays results for the causal effect of trade shocks on labor market distortions, i.e. where $y_{it} = \{\, \delta_{it}^{L}\,, |\delta_{it}^{L}|\}$. Columns 1-4 of Table 5 start with OLS regressions. They imply that import competition shocks, on average, *decrease* firms' labor market power, i.e. influence labor market distortions in a way that worsens the bargaining outcome of firms on their labor markets (δ_{it}^{L} rises). Simultaneously, OLS-regressions show an increase in the allocative efficiency of labor markets from import competition ($|\delta_{it}^{L}|$ falls). For export demand shocks, OLS predicts no significant effect.

However, since OLS suffers from an endogeneity biases, causal inference from OLS-results is not possible. I discuss the IV-solution below. Beforehand, note that for identifying the effects of trade shocks on labor market distortions, it is important that the competitiveness of intermediate inputs markets does not itself react to trade shocks. In columns 3 and 4 I account for those concerns by controlling for contemporaneous values of μ_{it}^{M}, which isolates reactions of intermediate inputs markets from responses of δ_{it}^{L} and $|\delta_{it}^{L}|$ to trade shocks. This ensures that reported coefficients on γ_{IMP} and γ_{EXP} are not caused by changes in the competitive benchmark. However, changes in product markups 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 trade shocks on δ_{it}^{L}, which affects δ_{it}^{L} through changes in μ_{it}^{M}. When interpreting my results, I therefore focus on specifications that do not control for firms' contemporaneous product markups and consider specifications controlling for μ_{it}^{M} as robustness checks. So far, controlling for μ_{it}^{M} leaves the results unchanged.

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

TABLE 5

LABOR MARKET DISTORTIONS AND TRADE SHOCKS								
	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}	98.38***	-39.15**	85.32***	-41.54**	219.20***	-42.61	187.10***	-48.41
	(26.24)	(18.48)	(23.80)	(18.30)	(61.00)	(42.54)	(53.46)	(42.99)
EXP_{it-1}^{CHN}	-15.36	31.17	-28.19	28.83	-425.40***	278.60***	-389.10***	285.20***
	(23.63)	(20.87)	(22.27)	(20.86)	(127.40)	(96.65)	(113.80)	(96.51)
μ_{it}^{M}	-	-	21,340***	3,891***	-	-	21,358***	3,868***
			(706.20)	(599.60)			(707.60)	(600.20)
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	108,826	108,826	108,826	108,826	108,826	108,826	108,826	108,826
R-squared	0.920	0.863	0.930	0.864	0.920	0.863	0.929	0.864
First-stage F-test	-	-	-	-	110.7	110.7	110.7	110.7
Number of firms	24,322	24,322	24,322	24,322	24,322	24,322	24,322	24,322

Notes: Table 5 reports results from estimating equation (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 of the 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.

The main concern when estimating equation (12) by OLS is that unobserved product demand and supply shocks simultaneously affect trade flows and domestic firms' labor demand.[16] To solve this identification problem, I apply an IV approach using lagged trade flows between China and countries similar to Germany as instruments for IMP_{it-1}^{CHN} and EXP_{it-1}^{CHN}. For this purpose, I define instruments in the following way: For every product, I first calculate the share of imports (exports) flowing from China (instrument group countries) to instrument group countries (China) in total imports (exports) of the instrument group countries. Identical to the construction of IMP_{it-1}^{CHN} and EXP_{it-1}^{CHN}, I subsequently 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 an instrument for local trade shocks exploits the fact that China's rise induces demand and supply shocks also for other trade partners. The instruments identify the exogenous component of rising Chinese product supply

[16] There are several mechanisms that create an endogeneity problem in line with the results reported in Table 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.

and demand by eliminating the effects of unobserved confounders that simultaneously influence trade flows between Germany and China as well as labor demand and economic performance of German firms (Dauth et al. 2014). 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, which would invalidate my identification (Autor et al. 2013; Dauth et al. 2014).[17]

Columns 5-8 in Table 5 present results from IV-regressions. Using IV-estimators increases the magnitude of nearly all coefficients. Notably, estimation by IV reveals that labor market distortions also respond to export demand shocks. According to column 5, a unit increase in import competition increases the share of rents that every full-time worker can capture from their firm relative to its output contribution by 219 euros, whereas a unit increase in export opportunities decreases this share by 425 euros. The increase of δ_{it}^{L} from import competition is not associated with a statistically significant effect on the allocative efficiency of labor markets (column 6). In contrast, export demand shocks decrease labor markets' allocative efficiency, implying that international trade, due to export participation of firms, can widen gaps between realized and potential output.[18] 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 by widening gaps between wages and the marginal product of labor, export demand shocks exert distorting effects, that, compared to the first best scenario, decrease allocative efficiency. 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 import competition shocks 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 mechanism working against this logic: Trade shocks may increase or decrease firms' profits stronger than their labor expenditures.[19] In fact, inspection of equation (5) shows that for given wage and employment levels δ_{it}^{L} decreases

[17] The instrument country group includes: Australia, New Zealand, Sweden, Norway, Japan, Great Britain, Canada, and Singapore. Results are robust to different specifications of the instrument country group.

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

[19] Note in this context, that I define my import measure as final product import competition rather than imports of intermediate inputs.

(increases) when output increases (decreases). Intuitively, the 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 trade shocks, 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 productivity shock) would affect ND- and PD-firms equally. To further understand the underlying within firm mechanisms, I will subsequently analyze PD- and ND-firms' adjustment processes to trade shocks in the next section.

Table 6 runs the regressions from Table 5 again on firms grouped according to their $t-1$ regime-type, i.e. firms are divided into PD- (Panel A) and ND-firms (Panel B). IV-results mostly confirm OLS-results for import competition shocks. Within PD-firms, a one unit increase in import competition increases the share of rents that workers can gain relative to their firm by 126 euros (column 5). For ND-firms that coefficient is larger (235 euros). Consistent with those findings, labor markets' allocative efficiency decreases (increases) from import shocks to 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 demand shocks on δ_{it}^{L} within ND-firms: A one unit increase in export opportunities increases firms' rents, relative to their workers, by 649 euros (per full-time worker). This translates into a huge loss in labor market efficiency that amounts to 5-6 percent of the median labor market distortion across all industries (Table 2). Interestingly, there is no effect of export demand shocks on labor market distortions within PD-firms. Quantitatively, labor market distortions respond *three to four times stronger* to ND-firm specific export demand shocks than to ND- or PD-firm specific import shocks.

TABLE 6

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

Panel A: PD-firms	PD-firms							
	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}	51.83**	44.65**	34.31*	30.24*	125.50***	103.50**	86.67**	71.63**
	(21.03)	(19.39)	(19.24)	(17.86)	(46.14)	(39.85)	(41.74)	(36.23)
EXP_{it-1}^{CHN}	-12.15	-12.19	-13.74	-13.50	-37.82	28.12	-64.49	6.180
	(26.27)	(22.00)	(23.38)	(19.68)	(121.80)	(97.81)	(112.00)	(89.53)
μ_{it}^M	-	-	15,395***	12,660***	-	-	15,384***	12,650***
			(413.30)	(352.90)			(413.60)	(353.00)
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	63,212	63,212	63,212	63,212	63,212	63,212	63,212	63,212
R-squared	0.834	0.846	0.858	0.865	0.833	0.846	0.858	0.865
First-stage F-test	-	-	-	-	72.14	72.14	72.12	72.12
Number of firms	16,483	16,483	16,483	16,483	16,483	16,483	16,483	16,483

Panel B: ND-firms	ND-firms							
	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}	181.00***	-163.80***	179.00***	-162.3***	234.80**	-214.80**	180.10*	-175.00*
	(49.89)	(48.83)	(49.17)	(50.07)	(117.30)	(106.20)	(103.70)	(99.72)
EXP_{it-1}^{CHN}	-38.31	45.65	-77.32*	74.04*	-648.50***	601.80***	-466.10**	469.00***
	(48.28)	(45.14)	(43.03)	(41.71)	(243.70)	(197.20)	(212.30)	(180.70)
μ_{it}^M	-	-	37,861***	-27,551***	-	-	37,964***	-27,656***
			(1,733)	(1,661)			(1,732)	(1,665)
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	41,297	41,297	41,297	41,297	41,297	41,297	41,297	41,297
R-squared	0.876	0.888	0.893	0.898	0.875	0.887	0.893	0.898
First-stage F-test	-	-	-	-	35.23	35.23	35.33	35.33
Number of firms	8,733	8,733	8,733	8,733	8,733	8,733	8,733	8,733

Notes: Table 6 reports results from estimating equation (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.

The findings of Table 6 confirm that existing labor market distortion structures are relevant for determining how trade shocks influence labor market distortions. Remember that ND-firms already pay their workers below optimal wages (vice versa for PD-firms). Hence, as export demand shocks increase ND-firms' labor market power without affecting δ_{it}^L in PD-firms, export demand shocks tend to raise inequality in labor market power between workers employed in PD- and ND-firms. I investigate this further in the online appendix E and, indeed, I find a positive causal relationship between industry level dispersion in δ_{it}^L and industry level export demand shocks. Moreover, the fact that export demand (import competition) shocks to ND-firms (PD-firms) increase existing labor market distortions implies that trade can widen gaps between potential and realized output. Import competition can however exert a labor market disciplining effect by decreasing ND-firms' labor market power. Consequently, it depends on existing domestic labor market power structures whether trade can improve or worsen absolute distortions on labor markets. This constitutes a novel margin for gains (losses) from trade. Abstracting from such interdependencies between labor market distortions and trade might misguide the judgment of distributional outcomes and total welfare gains from trade.

4.3 Firm adjustment to international trade

Wedges between workers output contribution and wages change, when, in response to trade shocks, 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 in this article suggest a domination of the latter in the case of Germany. This could be explained by firms and employees with labor market power that prevent a smooth labor expenditure adjustment to trade shocks and, thereby, influence the sharing of trade related profit losses and gains to their advantage. Interestingly, incomplete adjustment processes on labor markets bear a close analogy to recent findings on an incomplete pass-through of trade related productivity gains and exchange rate shocks to consumer prices (e.g. Amiti, Itskhoki, and 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. (forthcoming); 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.

TABLE 7

FIRM ADJUSTMENT AND TRADE SHOCKS,
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}	-0.0102***	-0.00792***	-0.000796	-0.0128***
	(0.00252)	(0.00206)	(0.000857)	(0.00470)
EXP_{it-1}^{CHN}	0.0262***	0.00909**	0.00987***	0.0176
	(0.00625)	(0.00436)	(0.00235)	(0.0108)
Firm $*$ Industry FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Observations	63,212	63,212	63,212	63,212
R-squared	0.982	0.981	0.939	0.941
First-stage F-test	73.23	73.23	73.23	73.23
Number of firms	16,483	16,483	16,483	16,483
Panel B: ND-firms	ND-firms			
	r_{it} (1)	l_{it} (2)	v_{it}^L (3)	χ_{it} (4)
IMP_{it-1}^{CHN}	0.00343	0.00200	0.00112	-0.0257
	(0.00438)	(0.00318)	(0.00213)	(0.00174)
EXP_{it-1}^{CHN}	0.0196***	0.000110	0.00164	0.136***
	(0.00708)	(0.00578)	(0.00360)	(0.0439)
Firm $*$ Industry FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Observations	41,297	41,297	41,297	41,297
R-squared	0.986	0.986	0.955	0.909
First-stage F-test	35.20	35.20	35.20	35.20
Number of firms	8,733	8,733	8,733	8,733

Notes: Table 7 reports results from estimating equation (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 firm level revenue deflated with an industry specific price index, FTE, average wages, and the non-logarithmized ratio between firm level intermediate input 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.

To investigate this further, Table 7 reports IV-regression results for the responses of firms' logged revenue deflated by an industry level deflator (r_{it}), logged FTE (l_{it}), logged average wages (v_{it}^L), as well as firms' ratio of intermediate to labor input expenditures (χ_{it}) to trade shocks. Results are separately reported for PD- (Panel A) and ND-firms (Panel B).

Indeed, Table 7 suggests that trade related profit changes are not perfectly passed-through into labor adjustments, which exerts distorting effects on domestic labor markets. Note, however, that the mechanism behind the effects of import competition shocks on ND-firms cannot be fully identified. This is not surprising, since 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 statistically highly significant decreases in revenue and employment levels in response to import competition. To fully understand the mechanism behind the previously reported positive effect of import competition on δ_{it}^{L} within PD-firms, note also that PD-firms decrease intermediate input expenditures stronger than labor expenditures in reaction to import shocks (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 seem to be partly protected from adverse shocks, which creates allocative inefficiencies.

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 do increase their intermediate input expenditures. This creates a wedge between adjustments in flexible commodities and labor input expenditures and implies 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 demand shocks. Importantly, export demand shocks 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 $|\delta_{it}^{L}|$ from export demand shocks to ND-firms are unlikely to be caused by institutional barriers or short run adjustment frictions that prevent an upward wage and employment adjustments by ND-firms.[20] Otherwise, PD-firms should be equally unable to adjust wages or employment upwards, which Table 7 disproves.

[20] 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 respectively by headcount and monthly salary.

5. ROBUSTNESS

This section tests the robustness of my results. In section 5.1 I rerun my entire estimation procedure without correcting for unobserved firm price variation. In section 5.2 I address concerns of endogeneity with respect to my instruments by constructing new instruments that exclusively rely on firms' first product portfolio observed in the data when aggregating product level trade flows to the firm level. Nearly all of my findings are qualitatively robust to both tests. Beyond that, the online appendix F 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 the periods t and $t-1$.

5.1 Ignoring firm level price variation

Table 8 reports results from estimating equation (12) by IV after rerunning my entire estimation procedure without controlling for unobserved firm level prices, i.e. omitting average wages and variables in $B_{it}(.)$ from equation (9). Table 8 first pools all firms (columns 1 and 2) and subsequently separates firms into $t-1$ PD-firms (columns 3 and 4) and ND-firms (columns 5 and 6). Although unobserved firm price variation is important for determining levels of labor market power (see online appendix D), it is less important for estimating the response of labor market distortions to trade shocks. 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 demand shocks on $|\delta_{it}^{L}|$ for the full sample of firms and the labor market disciplining effect of import competition shocks on ND-firms that decreased those firms' labor market power and increased labor markets' allocative efficiency. Particularly, in Table 8 I still find that import competition (export demand) shocks on PD-firms (ND-firms) decrease (increase) firms' labor market power, leading to a decline in labor market efficiency. Again, export demand shocks exert markedly stronger effects than import competition shocks.

TABLE 8

	All firms		PD-firms		ND-firms	
LABOR MARKET DISTORTIONS AND TRADE SHOCKS WHEN IGNORING FIRM LEVEL PRICE VARIATION						
	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}	181.60***	65.58*	132.70***	102.10**	5.607	18.93
	(49.20)	(33.77)	(45.74)	(43.44)	(78.48)	(65.30)
EXP_{it-1}^{CHN}	-329.8***	157.40	-58.00	-54.97	-584.50***	376.20**
	(115.60)	(99.79)	(121.30)	(114.80)	(217.60)	(191.30)
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	97,569	97,569	63,671	63,671	29,360	29,360
R-squared	0.921	0.856	0.851	0.861	0.855	0.868
First-stage F-test	86.29	86.29	48.98	48.98	26.02	26.02
Number of firms	22,549	22,584	16,438	16, 438	6,781	6,781

Notes: Table 8 reports IV-results from estimating equation (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.

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 (the product data already starts in 1995). 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 shocks. 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 9

Labor market distortions and trade shocks 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}	202.80***	-24.15	139.90**	127.10**	225.10	-207.10
	(75.73)	(49.71)	(67.45)	(58.85)	(143.40)	(140.90)
EXP_{it-1}^{CHN}	-330.50*	298.80**	-64.01	31.71	-819.70***	704.60***
	(173.80)	(130.00)	(190.20)	(141.50)	(309.70)	(281.00)
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	100,745	100,745	58,476	58,476	38,235	38,235
R-squared	0.920	0.863	0.833	0.846	0.875	0.887
First-stage F-test	60.83	60.83	64.10	64.10	15.13	15.13
Number of firms	22,568	22,568	15,260	15,260	8,106	8,106

Notes: Table 9 reports results from estimating equation (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, $\lvert\delta_{it}^{L}\rvert$. 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.

Again, Table 9 separately documents IV-results from using the new instruments for the full sample of firms as well as for $t-1$ PD- and ND-firms. Result reported in Table 9 are qualitatively similar to the baseline results (Tables 5 and 6). Like expected, standard errors go up using the new weighting scheme, which, however, has only a slight impact on the statistical significance of my results. Only the labor market disciplining effect from import competition, which also decreased ND-firms labor market power become insignificant when using the new instruments. However, the size of the associated coefficients is roughly equal to the corresponding ones in Table 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 in expectation to Chinese trade shocks are no concern for my empirical strategy. Notably, results from export demand shocks on ND-firms become even stronger when using the new instruments.

6. CONCLUSION

This article examines how trade shocks shape and interact 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 Chinese trade shocks on labor market imperfections in the German manufacturing sector, I find that firms with labor market power prevent an optimal pass-through of export profits gains to labor input expenditures, which 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 inefficiently towards firms and employees with labor market power and decrease the allocative efficiency of labor markets. In contrast, evidence for labor market disciplining effects is extremely sensitive to the employed model specifications.

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 bears a clear importance for 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 similarly be 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 hope that this article lends itself helpful in encouraging fruitful discussions on those and related questions.

REFERENCES

ACKERBERG, D. AND J. HAHN, "Some Non-Parametric Identification Results using Timing and Information Set Assumptions," mimeo, 2015.

AHSAN, R. N. AND D. MITRA, "Trade liberalization and labor's slice of the pie: Evidence from Indian firms," *Journal of Development Economics 108 (2014)*, 1-16.

ARKOLAKIS, C., A. COSTINOT, D. DONALDSON, AND A. RODRÍGUEZ-CLARE, "The Elusive Pro-Competitive Effects of Trade," *The Review of Economic Studies* (forthcoming).

AUTOR, D. H., D. DORN, AND G. H. HANSON, "The China Syndrome: Local Labor Market Effects of Import Competition in the United States," *The American Economic Review 103* (2013), 2121-2168.

AUTOR, D. H., D. DORN, AND G. H. HANSON, "The China Shock: Learning from Labor-Market Adjustment to Large Changes in Trade," *Annual Review of Economics 8* (2016), 205-240.

AUTOR, D. H., D. DORN, G. H. HANSON, AND K. MAJLESI, "Importing Political Polarization?," NBER Working Paper w22637, National Bureau of Economic Research, 2016.

AUTOR, D. H., D. DORN, L. F. KATZ, C. PATTERSON, AND J. VAN REENEN, "The fall of the labor share and the rise of superstar firms," NBER Working Paper w23396, National Bureau of Economic Research, 2017.

AUTOR, D. H., D. DORN, G. H. HANSON, AND J. SONG, "Trade adjustment: Worker-level evidence," *The Quarterly Journal of Economics 129* (2014), 1799-1860.

AMITI, M., O. ITSKHOKI, AND J. KONINGS, "Importers, exporters, and exchange rate disconnect," *The American Economic Review 104* (2014), 1942-1978.

ARTUÇ, E., S. CHAUDHURI, AND J. MCLAREN, "Trade Shocks and Labor Adjustment: A Structural Empirical Approach," *The American Economic Review 100* (2010), 1008-1045.

AZAR, J. A., I. MARINESCU, M. I. STEINBAUM, AND B. TASKA, "Concentration in US labor markets: Evidence from online vacancy data," NBER Working Paper w24395, National Bureau of Economic Research, 2018.

BRÄUER, R., M. MERTENS, AND V. SLAVTCHEV, "Import Competition and Multi-Product Firms Productivity," mimeo, Halle Institute for Economic Research, 2018.

BERNARD, A. B., S. J. REDDING, AND P. K. SCHOTT, "Multiproduct firms and trade liberalization," *The Quarterly Journal of Economics 126* (2011), 1271-1318.

BERRY, S. T., "Estimating discrete-choice models of product differentiation," *The RAND Journal of Economics 25 (1994)*, 242-262.

BOULHOL, H., "Do capital market and trade liberalization trigger labor market deregulation?," *Journal of International Economics*, *77* (2009), 223-233.

BOULHOL, H., S. DOBBELAERE, AND S. MAIOLI, "Imports as product and labour market discipline," *British Journal of Industrial Relations 49* (2011), 331-361.

CALIENDO, L. AND E. ROSSI-HANSBERG, "The impact of trade on organization and productivity," *The Quarterly Journal of Economics 127* (2012), 1393-1467.

CALIENDO, L., F. MONTE, AND E. ROSSI-HANSBERG, "Exporting and Organizational Change," NBER Working Paper w23630, National Bureau of Economic Research, 2017.

CARLUCCIO, J., D. FOUGÈRE, AND E. GAUTIER, "Trade, wages, and collective bargaining," Rue de la Banque No. 16, Banque de France, 2016

COŞAR, A. K., N. GUNER, AND J. TYBOUT, "Firm dynamics, job turnover, and wage distributions in an open economy," *The American Economic Review 106* (2016), 625-663.

DAUTH, W., S. FINDEISEN, AND J. SÜDEKUM, "The rise of the East and the Far East: German labor markets and trade integration," *Journal of the European Economic Association 12* (2014), 1643-1675.

DAUTH, W., S. FINDEISEN, AND J. SÜDEKUM, "Adjusting to Globalization-Evidence from Worker-Establishment Matches in Germany," CEPR Discussion Papers No. 11045, Center for Economic Policy Research, 2016.

DE LOECKER, J., "Detecting learning by exporting," *American Economic Journal: Microeconomics 5* (2013), 1-21.

DE LOECKER, J., P. K. GOLDBERG, A. K. KHANDELWAL, AND N. PAVCNIK, "Prices, markups, and trade reform," *Econometrica 84* (2016), 445-510.

DE LOECKER, J. AND P. T. SCOTT, "Estimating market power Evidence from the US Brewing Industry" NBER Working Paper w22957, National Bureau of Economic Research, 2016.

DE LOECKER, J. AND F. WARZYNSKI, "Markups and firm level export status," *The American Economic Review 102* (2012), 2437-2471.

DIPPEL, C., R. GOLD, S. HEBLICH, AND R. PINTO, "Instrumental Variables and Causal Mechanisms: Unpacking The Effect of Trade on Workers and Voters," NBER Working Paper w23209, National Bureau of Economic Research, 2017.

DIX-CARNEIRO, R., "Trade liberalization and labor market dynamics," *Econometrica 82* (2014), 825-885.

DOBBELAERE, S. AND K. KIYOTA, "Labor market imperfections, markups and productivity in multinationals and exporters," *Labour Economics (forthcoming).*

DOBBELAERE, S., K. KIYOTA, AND J. MAIRESSE, "Product and labor market imperfections and scale economies: Micro-evidence on France, Japan and the Netherlands," *Journal of Comparative Economics 43* (2015), 290-322.

DOBBELAERE, S., R. LAUTERBACH, AND J. MAIRESSE, "Micro-evidence on product and labor market regime differences between Chile and France," *International Journal of Manpower 37* (2016), 229-252.

DOBBELAERE, S. AND J. MAIRESSE, "Panel data estimates of the production function and product and labor market imperfections," *Journal of Applied Econometrics 28* (2013), 1-46.

ECKEL, C. AND S. R. YEAPLE, "Too Much of a Good Thing? Exporters, Multiproduct Firms and Labor Market Imperfections," NBER Working Paper w23834, National Bureau of Economic Research, 2017.

EGGER, H. AND U. KREICKEMEIER, "Firm heterogeneity and the labor market effects of trade liberalization," *International Economic Review 50* (2009), 187-216.

ESLAVA, M., J. HALTIWANGER, A. KUGLER, AND M. KUGLER, "The effects of structural reforms on productivity and profitability enhancing reallocation: evidence from Colombia," *Journal of Development Economics 75* (2004), 333-371.

HASAN, R., D. MITRA, AND K. V. RAMASWAMY, "Trade reforms, labor regulations, and labor-demand elasticities: Empirical evidence from India," *The Review of Economics and Statistics 89* (2007), 466-481.

HELPMAN, E., O. ITSKHOKI, M. A. MUENDLER, AND S. J. REDDING, "Trade and inequality: From theory to estimation," *The Review of Economic Studies 84* (2017), 357-405.

HORNSTEIN, A., P. KRUSELL, AND G. L. VIOLANTE, "The effects of technical change on labor market inequalities," in P. Aghion and S. N. Durlauf, eds., *Handbook of Economic Growth* (Amsterdam: Elsevier, North-Holland, 2005), 1275-1370.

KAMBOUROV, G, "Labour market regulations and the sectoral reallocation of workers: The case of trade reforms," *The Review of Economic Studies 76* (2009), 1321-1358.

LEVINSOHN, J. AND A. PETRIN, "Estimating Production Functions Using Inputs to Control for Unobservables," *Review of Economic Studies 70* (2003), 317-341.

LU, Y., Y. SUGITA, L. ZHU, "Wage Markdowns and FDI Liberalization," mimeo, 2018.

MANNING, A., *Monopsony in motion: Imperfect competition in labor markets* (Princeton: Princeton University Press, 2003)

MARINESCU, I. E. AND H. HOVENKAMP, "Anticompetitive Mergers in Labor Markets," *mimeo, University of Pennsylvania Law School, 2018*

MAYER, T., M. J. MELITZ, AND G. I. OTTAVIANO, "Market size, competition, and the product mix of exporters," *The American Economic Review 104* (2014), 495-536.

MCDONALD, I. M. AND R. M. SOLOW, "Wage bargaining and employment," *The American Economic Review 71* (1981), 896-908.

MELITZ, M. J., "The impact of trade on intra- industry reallocations and aggregate industry productivity," *Econometrica 71* (2003), 1695-1725.

MION, G. AND L. ZHU, "Import competition from and offshoring to China: A curse or blessing for firms?," *Journal of International Economics 89* (2013), 202-215.

MÜLLER, S., "Capital stock approximation using firm level panel data," *Jahrbücher für Nationalökonomie und Statistik 228* (2008), 357-371.

NAIDU, S., E. A. POSNER, AND E. G. WEYL, "Antitrust Remedies for Labor Market Power," mimeo, Coase-Sandor Institute for Law and Economics Research, University of Chicago, 2018

NESTA, L. AND S. SCHIAVO, "International Competition and Rent Sharing in French Manufacturing," Sciences PO OFCE Working Paper n. 14, Sciences PO, 2018.

NICKELL, S., "Product markets and labour markets," *Labour Economics 6* (1999), 1-20.

OECD, "OECD Indicators of Employment Protection," http://www.oecd.org, 2018.

OLLEY, S. AND A. PAKES, "The dynamics of productivity in the telecommunications equipment industry," *Econometrica 64* (1996), 1263-97.

PETRIN, A. AND J. SIVADASAN, "Estimating lost output from allocative inefficiency, with an application to Chile and firing costs," *Review of Economics and Statistics 95* (2013), 286-301.

REBITZER, J. B. AND L. J. TAYLOR, "A model of dual labor markets when product demand is uncertain," *The Quarterly Journal of Economics 106* (1991), 1373-1383.

RODRIK, D., "Has globalization gone too far?," *California Management Review 39* (1997), 29-53.

TORTAROLO, D. AND R. D. ZARATE, "Measuring Imperfect Competition in Product and Labor Markets. An Empirical Analysis using Firm-level Production Data," Discussion Paper No.1152, CAF Development Bank Of Latin America, 2018

VALMARI, N., "Estimating Production Functions of Multiproduct Firms," ETLA Working Papers No. 37, The Research Institute of the Finnish Economy, 2016

VERHOOGEN, E. A. "Trade, quality upgrading, and wage inequality in the Mexican manufacturing sector," *The Quarterly Journal of Economics 123* (2008), 489-530.

WEINBERGER, A., "Markups and Misallocation with Evidence from an Exchange Rate Appreciation" mimeo, 2017

WOOLDRIDGE, J. M., "On estimating firm level production functions using proxy variables to control for unobservables," *Economics Letters 104* (2009), 112-114.

YI, M., S. MÜLLER, AND J. STEGMAIER, "Industry Mix, Local Labor Markets, and the Incidence of Trade Shocks," *mimeo, 2017.*

TABLES – SEPARATELY

TABLE 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	24,013	0.63	0.10	0.16	0.89
17 Textiles	5,908	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	1,327	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	4,746	0.46	0.15	0.38	1.09
24 Chemicals and chemical products	11,632	0.71	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	9,567	0.66	0.32	0.10	1.09
27 Basic metals	7,112	0.68	0.31	0.05	1.02
28 Fabricated metal products	23,866	0.59	0.31	0.12	0.99
29 Machinery and equipment	28,216	0.61	0.37	0.08	1.05
30 Electrical and optical equipment	1,432	0.58	0.32	0.07	0.93
31 Electrical machinery and apparatus	10,401	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	7,890	0.59	0.27	0.19	1.07
34 Motor vehicles and trailers	6,709	0.68	0.31	0.26	1.27
35 Transport equipment	2,939	0.64	0.31	0.09	1.09
36 Furniture manufacturing	8,001	0.65	0.28	0.05	0.96
Across all industries	180,317	0.63	0.28	0.10	1.01

Notes: Table 1 reports median output elasticities from estimating the production function (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 2

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

	δ_{it}^{L}	$\lvert\delta_{it}^{L}\rvert$	V_{it}^{L}	$(\mu_{it}^{M} - \mu_{it}^{L})$	Observations
Sector	(1)	(2)	(3)	(4)	(6)
15 Food products and beverages	12,506.28	12,516.81	24,463.46	0.50	17,977
17 Textiles	8.84	8,849.06	31,651.93	0.00	5,772
18 Apparel, dressing, and dyeing of fur	4,763.23	8,819.77	29,988.74	0.19	1,766
19 Leather and leather products	8,910.00	9,740.76	27,000.33	0.38	936
20 Wood and wood products	1,411.28	6,745.56	31,496.06	0.05	4,741
21 Pulp, paper, and paper products	-6,827.43	12,517.63	38,609.97	-0.20	4,107
22 Publishing and printing	-6,746.72	21,638.76	37,519.39	-0.14	1,475
24 Chemicals and chemical products	-1,943.86	11,461.76	46,002.97	-0.05	11,483
25 Rubber and plastic products	5,569.34	6,780.32	34,616.85	0.17	11,214
26 Other non-metallic mineral products	-2,881.98	9,698.15	36,840.14	-0.09	8,947
27 Basic metals	-4,021.13	12,418.3	40,972.91	-0.11	5,898
28 Fabricated metal products	5,395.74	11,015.09	36,130.12	0.18	23,672
29 Machinery and equipment	1,722.88	12,593.54	42,261.64	0.05	27,790
30 Electrical and optical equipment	-146.56	17,318.68	41,148.26	0.00	804
31 Electrical machinery and apparatus	1,351.52	12,736.70	37,315.81	0.04	10,131
32 Radio, television, and communication	3,872.30	16,182.19	35,551.46	0.13	2,387
33 Medical and precision instruments	13,465.69	16,826.59	38,140.48	0.47	7,506
34 Motor vehicles and trailers	-1,011.10	20,231.55	37,436.22	-0.03	5,391
35 Transport equipment	6,278.08	17,099.38	38,518.78	0.19	2,005
36 Furniture manufacturing	6,410.18	7,701.79	30,343.83	0.24	5,723
Across all industries	4,371.89	11,434.63	36,521.04	0.14	159,725

Notes: Table 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 markups based on firms' intermediate and labor input decision in the associated industry. 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.

TABLE 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	96.53	3.47	18,468
17 Textiles	50.09	49.91	5,778
18 Apparel, dressing, and dyeing of fur	69.16	30.84	1,767
19 Leather and leather products	80.02	19.98	936
20 Wood and wood products	55.49	44.51	4,759
21 Pulp, paper, and paper products	33.55	66.45	4,217
22 Publishing and printing	40.34	59.66	1,688
24 Chemicals and chemical products	45.38	54.62	11,581
25 Rubber and plastic products	76.48	23.52	11,279
26 Other non-metallic mineral products	42.31	57.69	8,963
27 Basic metals	40.95	59.05	5,963
28 Fabricated metal products	64.97	35.03	23,803
29 Machinery and equipment	53.62	46.38	28,202
30 Electrical and optical equipment	47.52	52.48	909
31 Electrical machinery and apparatus	52.88	47.12	10,265
32 Radio, television, and communication	55.70	44.30	2,684
33 Medical and precision instruments	78.08	21.92	7,760
34 Motor vehicles and trailers	44.36	55.64	6,095
35 Transport equipment	58.43	41.57	2,100
36 Furniture manufacturing	76.86	23.14	5,766
Across all industries	61.30	38.70	162,983

Notes: Table 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.

TABLE 4

DIFFERENCES BETWEEN PD- AND ND-FIRMS

	Wages (1)	FTE (2)	Output (3)	Markups (4)	Capital per FTE (5)	Value added per FTE (6)
PD_{it}	0.0568***	-0.964***	-1.289***	0.170***	-0.470***	-0.0563***
	(0.00465)	(0.0144)	(0.0188)	(0.00302)	(0.0117)	(0.00948)
Industry FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
Observations	146.240	146.240	146.240	146.240	146.240	146.240
R-squared	0.274	0.239	0.274	0.265	0.161	0.061
Number of firms	31,934	31,934	31,934	31,934	31,934	31,934

Notes: Table 4 reports results from estimating equation (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.

TABLE 5

LABOR MARKET DISTORTIONS AND TRADE SHOCKS								
	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}	98.38***	-39.15**	85.32***	-41.54**	219.20***	-42.61	187.10***	-48.41
	(26.24)	(18.48)	(23.80)	(18.30)	(61.00)	(42.54)	(53.46)	(42.99)
EXP_{it-1}^{CHN}	-15.36	31.17	-28.19	28.83	-425.40***	278.60***	-389.10***	285.20***
	(23.63)	(20.87)	(22.27)	(20.86)	(127.40)	(96.65)	(113.80)	(96.51)
μ_{it}^{M}	-	-	21,340***	3,891***	-	-	21,358***	3,868***
			(706.20)	(599.60)			(707.60)	(600.20)
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	108,826	108,826	108,826	108,826	108,826	108,826	108,826	108,826
R-squared	0.920	0.863	0.930	0.864	0.920	0.863	0.929	0.864
First-stage F-test	-	-	-	-	110.7	110.7	110.7	110.7
Number of firms	24,322	24,322	24,322	24,322	24,322	24,322	24,322	24,322

Notes: Table 5 reports results from estimating equation (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 of the 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.

TABLE 6

LABOR MARKET DISTORTIONS AND TRADE SHOCKS,
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}	51.83**	44.65**	34.31*	30.24*	125.50***	103.50**	86.67**	71.63**
	(21.03)	(19.39)	(19.24)	(17.86)	(46.14)	(39.85)	(41.74)	(36.23)
EXP_{it-1}^{CHN}	-12.15	-12.19	-13.74	-13.50	-37.82	28.12	-64.49	6.180
	(26.27)	(22.00)	(23.38)	(19.68)	(121.80)	(97.81)	(112.00)	(89.53)
μ_{it}^{M}	-	-	15,395***	12,660***	-	-	15,384***	12,650***
			(413.30)	(352.90)			(413.60)	(353.00)
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	63,212	63,212	63,212	63,212	63,212	63,212	63,212	63,212
R-squared	0.834	0.846	0.858	0.865	0.833	0.846	0.858	0.865
First-stage F-test	-	-	-	-	72.14	72.14	72.12	72.12
Number of firms	16,483	16,483	16,483	16,483	16,483	16,483	16,483	16,483

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}	181.00***	-163.80***	179.00***	-162.3***	234.80**	-214.80**	180.10*	-175.00*
	(49.89)	(48.83)	(49.17)	(50.07)	(117.30)	(106.20)	(103.70)	(99.72)
EXP_{it-1}^{CHN}	-38.31	45.65	-77.32*	74.04*	-648.50***	601.80***	-466.10**	469.00***
	(48.28)	(45.14)	(43.03)	(41.71)	(243.70)	(197.20)	(212.30)	(180.70)
μ_{it}^{M}	-	-	37,861***	-27,551***	-	-	37,964***	-27,656***
			(1,733)	(1,661)			(1,732)	(1,665)
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	41,297	41,297	41,297	41,297	41,297	41,297	41,297	41,297
R-squared	0.876	0.888	0.893	0.898	0.875	0.887	0.893	0.898
First-stage F-test	-	-	-	-	35.23	35.23	35.33	35.33
Number of firms	8,733	8,733	8,733	8,733	8,733	8,733	8,733	8,733

Notes: Table 6 reports results from estimating equation (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.

TABLE 7

FIRM ADJUSTMENT AND TRADE SHOCKS,
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}	-0.0102***	-0.00792***	-0.000796	-0.0128***
	(0.00252)	(0.00206)	(0.000857)	(0.00470)
EXP_{it-1}^{CHN}	0.0262***	0.00909**	0.00987***	0.0176
	(0.00625)	(0.00436)	(0.00235)	(0.0108)
Firm $*$ Industry FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Observations	63,212	63,212	63,212	63,212
R-squared	0.982	0.981	0.939	0.941
First-stage F-test	73.23	73.23	73.23	73.23
Number of firms	16,483	16,483	16,483	16,483

Panel B: ND-firms	ND-firms			
	r_{it} (1)	l_{it} (2)	v_{it}^{L} (3)	χ_{it} (4)
IMP_{it-1}^{CHN}	0.00343	0.00200	0.00112	-0.0257
	(0.00438)	(0.00318)	(0.00213)	(0.00174)
EXP_{it-1}^{CHN}	0.0196***	0.000110	0.00164	0.136***
	(0.00708)	(0.00578)	(0.00360)	(0.0439)
Firm $*$ Industry FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Observations	41,297	41,297	41,297	41,297
R-squared	0.986	0.986	0.955	0.909
First-stage F-test	35.20	35.20	35.20	35.20
Number of firms	8,733	8,733	8,733	8,733

Notes: Table 7 reports results from estimating equation (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 firm level revenue deflated with an industry specific price index, FTE, average wages, and the non-logarithmized ratio between firm level intermediate input 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.

TABLE 8

LABOR MARKET DISTORTIONS AND TRADE SHOCKS WHEN IGNORING FIRM LEVEL PRICE VARIATION						
	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}	181.60***	65.58*	132.70***	102.10**	5.607	18.93
	(49.20)	(33.77)	(45.74)	(43.44)	(78.48)	(65.30)
EXP_{it-1}^{CHN}	-329.8***	157.40	-58.00	-54.97	-584.50***	376.20**
	(115.60)	(99.79)	(121.30)	(114.80)	(217.60)	(191.30)
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	97,569	97,569	63,671	63,671	29,360	29,360
R-squared	0.921	0.856	0.851	0.861	0.855	0.868
First-stage F-test	86.29	86.29	48.98	48.98	26.02	26.02
Number of firms	22,549	22,584	16,438	16, 438	6,781	6,781

Notes: Table 8 reports IV-results from estimating equation (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 9

LABOR MARKET DISTORTIONS AND TRADE SHOCKS
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}	202.80***	-24.15	139.90**	127.10**	225.10	-207.10
	(75.73)	(49.71)	(67.45)	(58.85)	(143.40)	(140.90)
EXP_{it-1}^{CHN}	-330.50*	298.80**	-64.01	31.71	-819.70***	704.60***
	(173.80)	(130.00)	(190.20)	(141.50)	(309.70)	(281.00)
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	100,745	100,745	58,476	58,476	38,235	38,235
R-squared	0.920	0.863	0.833	0.846	0.875	0.887
First-stage F-test	60.83	60.83	64.10	64.10	15.13	15.13
Number of firms	22,568	22,568	15,260	15,260	8,106	8,106

Notes: Table 9 reports results from estimating equation (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.

ONLINE APPENDIX – NOT FOR PUBLICATION

Appendix A: Firm characteristics and the evolution trade measures

TABLE A.1

SUMMARY STATISTICS FOR SAMPLE FIRMS

Variable	Mean (1)	Sd (2)	P25 (3)	Median (4)	P75 (5)	Observations (6)
Revenue in thousand Euros	50,600	258,000	4,828	11,600	34,500	159,725
Deflated capital stock in thousand Euros	31,600	166,000	2,110	5,982	19,700	159,725
Intermediate inputs in thousand Euros	33,400	183,000	2,560	6,810	21,700	159,725
Full time equivalent (FTE)	237.23	834.00	43.50	86.00	202.00	159,725
Total wage bill in thousand Euros	12,100	56,300	1,535	3,305	8,725	159,725
Firm level average nominal wage	41,252	13,398	31,658	40,460	49,668	159,725
Deflated capital over FTE	98,694	107,517	37,322	67,958	121,831	159,725
Log of real value added over FTE	10.81	0.50	10.51	10.82	11.11	159,638
Log of firm price index	0.08	0.21	0	0.06	0.18	159,698
Log of revenue weighted sum of product market shares (revenue based)	0.95	1.97	-0.38	1.08	2.47	159, 725
Log of revenue weighted sum of product market shares (quantity based)	0.68	2.37	-0.88	0.95	2.54	130,371
Number of products	3.52	6.98	1	2	4	159,725
Dummy for export status	0.77	0.42	1	1	1	159,725
Dummy for R&D activities	0.34	0.47	0	0	1	159,725
Worker outsourcing rate	2.78	5.58	0	0.37	3.16	159,725
Markup (intermediate input decision)	1.10	0.22	0.96	1.06	1.18	159,725
Markup (labor input decision)	1.02	0.50	0.69	0.94	1.26	159,725
Labor market power parameter	113	21,252	-7,507	4,372	13,215	159,725
Absolute labor market power parameter	15,209	15,209	5,429	11,435	19,998	159,725
Import competition measure (firm level)	1.67	5.33	0	0.32	2.97	154,824
Export opportunity measure (firm level)	0.89	2.59	0	0.04	0.68	154,824

Notes: Table A.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.

Appendix B: Deriving a parameter for labor market distortions

In the following I first derive equation (5) form the main text and then discuss how this expression is linked to the framework of Dobbelaere and Mairesse (2013). Distortions are given by:

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

Since 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 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 (5) of the main text.

De Loecker and Warzynski (2012) and Dobbelaere and Kiyota (forthcoming) show that one can derive an expression for firm level markups based on the firm's optimal input decision for any flexible input whose associated input market is also competitive. In this 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, since observed labor expenditures deviate from optimal labor expenditures. When expressing labor market distortions in monetary terms this can be highlighted as:

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

where observed wages, V_{it}^L, deviate from optimal wages, $V_{it}^{L^*} = MRPL_{it}$, by the degree of labor market distortions. Dobbelaere and 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 and 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.[21] Interestingly, reformulating the condition $\mu_{it}^M = \mu_{it}^L$ gives:

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

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

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

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

Note that equation (B.9) is identical to equation (B.4) and equation (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 with μ_{it}^M (as in Dobbelaere and 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:

[21] In fact, Dobbelaere and Mairesse (2013) originally apply this framework to the industry level. A firm level application can for instance be found in Dobbelaere and Kiyota (forthcoming).

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

Appendix C: 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 trade shocks 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 will additionally show that markups calculated by using firms' intermediate input decision, μ_{it}^M, are less dispersed than markups based on firms' labor input decision, μ_{it}^L. Figure C.1 shows the respective density plot for both markups.

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

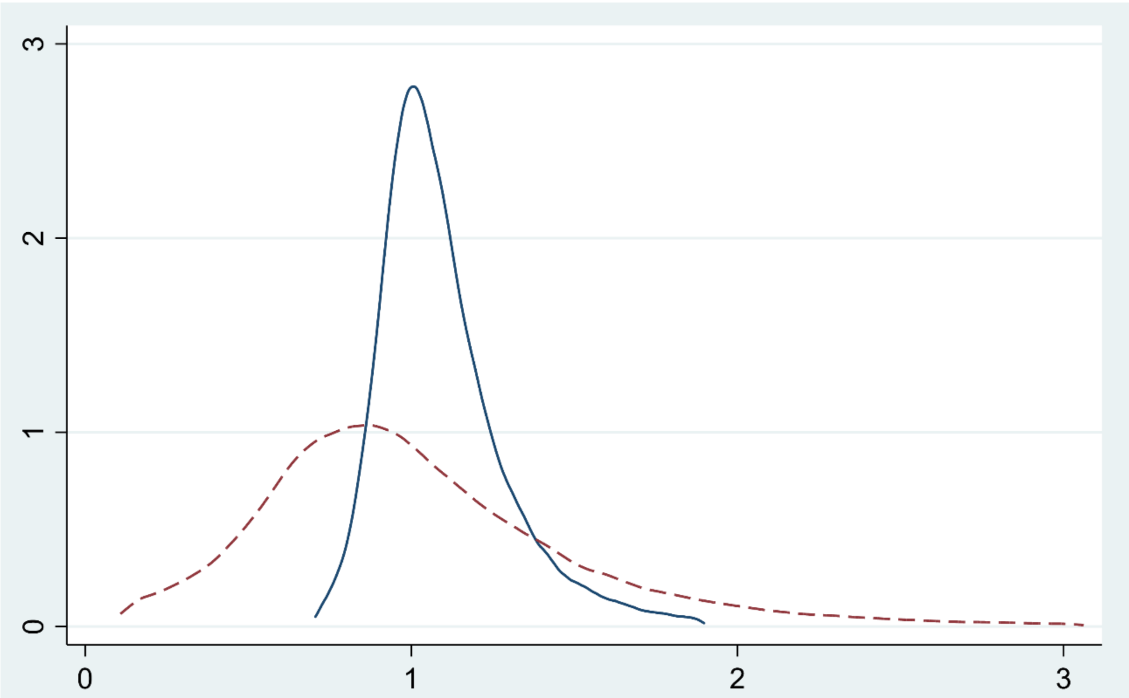

FIGURE C.1 – Kernel density plots for in the sample. Outliers below and above the 1st and the 99th percentiles are trimmed.

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 markups, 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). Instead, as Figure C.1 illustrates, the extreme markup values of μ_{it}^L can only be rationalized when one considers that μ_{it}^L also (largely) contains labor market distortions. Figure C.2

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

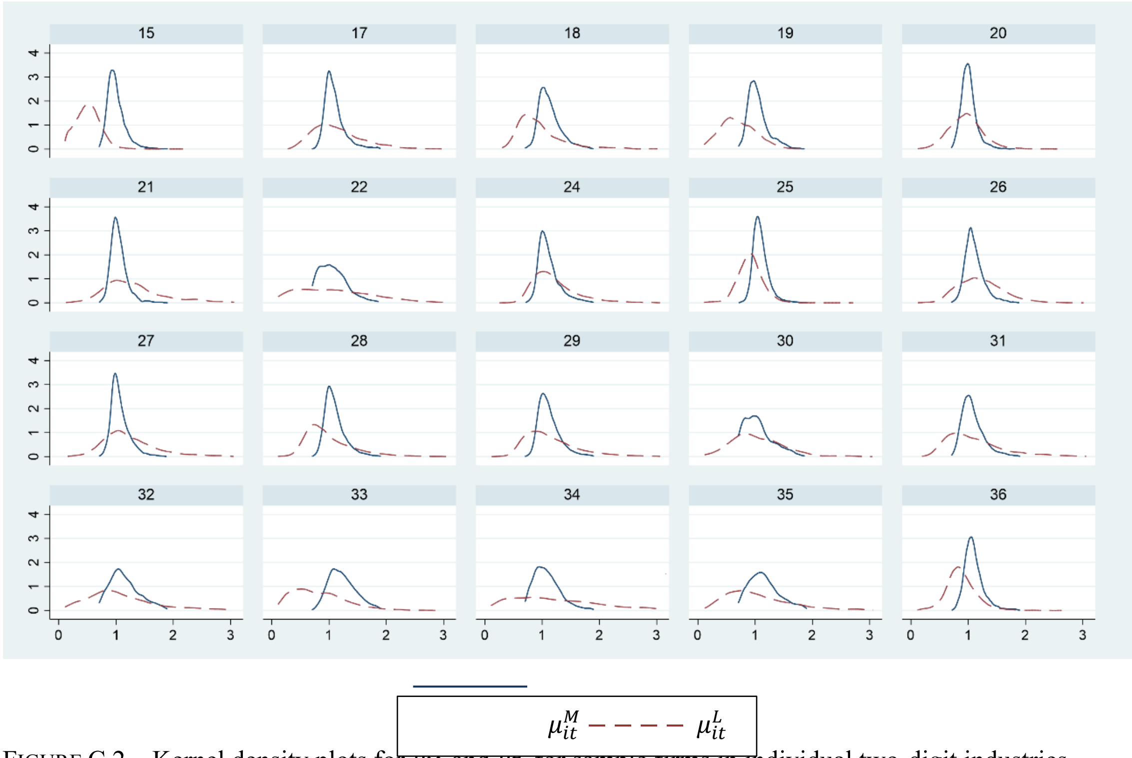

FIGURE C.2 – Kernel density plots for μ_{it}^M and μ_{it}^L for sample firms in individual two-digit industries. Outliers below and above the 1st and the 99th percentiles are trimmed.

Appendix D: 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 D.1 compares median output elasticities from estimating the production function with and without correcting for unobserved price variation. Columns 1-4 are identical with the main text. Columns 5-8 report output elasticities derived from a production function where firm revenue (left-hand side variable) is 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 (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 price variation, 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 the returns to scale and the output elasticity of intermediate inputs are higher, whereas associated 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 that are below zero. In total, the number of observations with negative output elasticities dramatically increases when I ignore firm level price variation.

TABLE D.1

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	0.71	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	1.09	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	0.99	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	1.47
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	0.11	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 D.1 reports median output elasticities from estimating the production function (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.

Figure D.1 shows the corresponding difference in the number of negative output elasticities between the baseline specification, where I control for firm level input and output prices, and the specification where I ignore them. Over the entire estimation period the blue solid line, indicating the number of negative output elasticities when I ignore firm level variation in prices, roughly doubles the level of the red dashed line, which refers to the baseline specification of the main text. In sum, I estimate 17,334 out of 180,317 negative output elasticities in my baseline specification (equals 9.6%) against 33,175 out of 180,682 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.

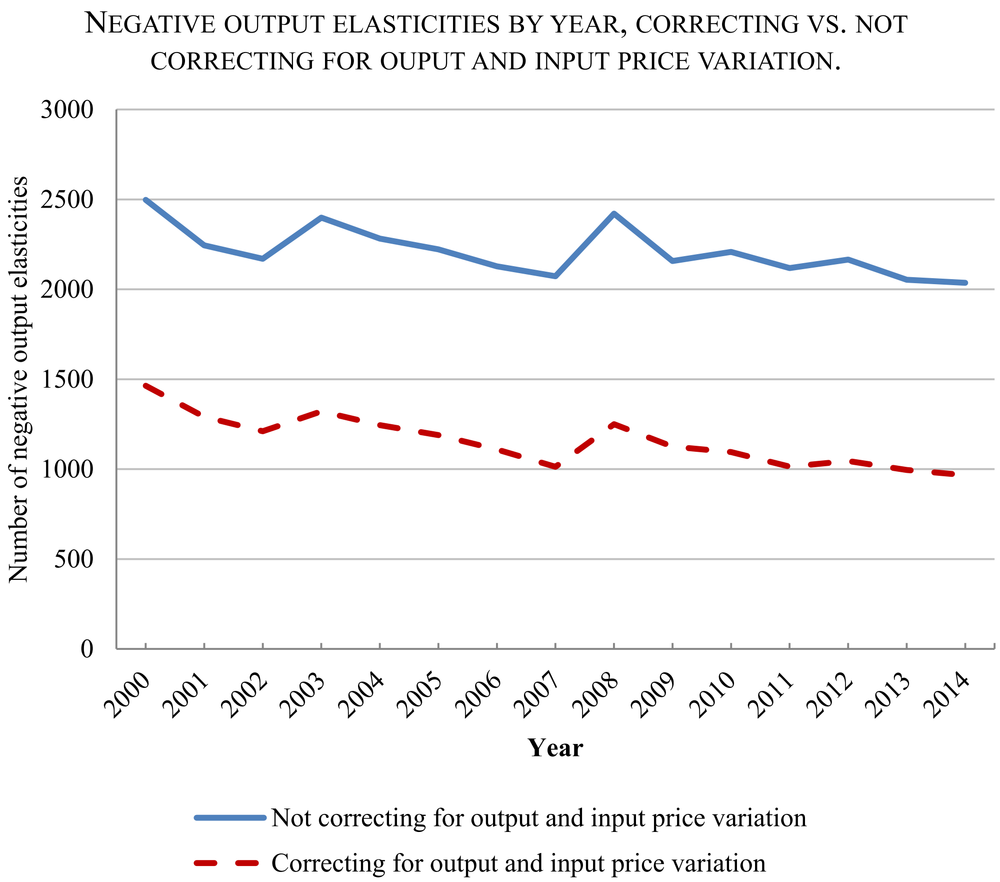

FIGURE D.1 – Total number of negative output elasticities by year, when the production function (9) is estimated with and without correcting for unobserved output and input price variation.

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, and 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.[22] 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).

TABLE D.2

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

	Correcting for output and input price variation		Not correcting for output and input 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	12,506.28	12,516.81	11,494.39	12,050.44
17 Textiles	8.84	8,849.06	7,856.91	9,277.78
18 Apparel, dressing, and dyeing of fur	4,763.23	8,819.77	1,111.42	8,456.47
19 Leather and leather products	8,910.00	9,740.76	12,550.60	13,311.65
20 Wood and wood products	1,411.28	6,745.56	4,570.85	6,648.72
21 Pulp, paper, and paper products	-6,827.43	12,517.63	6,508.46	9,336.33
22 Publishing and printing	-6,746.72	21,638.76	12,479.06	14,323.55
23 Coke, refined petroleum products and nuclear fuel	-	-	6,785.66	21,364.68
24 Chemicals and chemical products	-1,943.86	11,461.76	-659.24	14,309.34
25 Rubber and plastic products	5,569.34	6,780.32	8,775.97	9,501.58
26 Other non-metallic mineral products	-2,881.98	9,698.15	-2,997.39	10,945.70
27 Basic metals	-4021.13	12,418.3	-3,052.90	13,825.92
28 Fabricated metal products	5,395.74	11,015.09	6,339.19	10,173.59
29 Machinery and equipment	1,722.88	12,593.54	4,004.80	12,779.47
30 Electrical and optical equipment	-146.56	17,318.68	15,681.08	19,551.78
31 Electrical machinery and apparatus	1,351.52	12,736.70	8,242.89	13,705.49
32 Radio, television, and communication	3,872.30	16,182.19	11,230.33	13,831.91
33 Medical and precision instruments	13,465.69	16,826.59	8,486.28	9,562.55
34 Motor vehicles and trailers	-1011.10	20,231.55	12,455.16	19,302.95
35 Transport equipment	6,278.08	17,099.38	16,672.96	17,388.86
36 Furniture manufacturing	6,410.18	7,701.79	8,496.32	9,976.14
Total	4,371.89	11,434.63	6,835.87	11,662.82

Table D.2 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.

Next, I turn to the labor market imperfection parameter, δ_{it}^{L}, which implies the degree of labor market distortions at the firm level. Many studies use such a

[22] 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 and Goldberg (2014), output price and input price biases tend to work against each other, i.e. they partly offset each other.

parameter to classify industry or firm level labor markets into efficient bargaining (EB) and monopsonistic (MO) wage setting regimes.[23] In this study I essentially classify firms in the same way but, as discussed in the main text, I prefer to call EB- and MO-firms respectively positively distorted (PD) and negatively distorted (ND) firms. Regularly, most studies find an relatively low amount of ND-regimes, concluding that workers have a strong position on their labor market (e.g. Dobbelaere et al. 2015; Dobbelaere et al. 2016).[24] However, to the best of my knowledge, no study simultaneously takes into account the potential bias emerging from unobserved input and output price variation in their classification.

Table D.2 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 D.3 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.

[23] E.g. Dobbelaere and Mairesse (2013); Dobbelaere, Kiyota, and Mairesse (2015); Dobbelaere, Lauterbach, and Mairesse (2016).

[24] The only exception I am aware of is the case study for Netherlands in Dobbelaere et al. (2015). However, as they discuss, their classification results strongly depend on the applied classification method.

TABLE D.3

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	96.53	3.47	18,468	91.19	8.81	15,589
17 Textiles	50.09	49.91	5,778	80.36	19.64	5,519
18 Apparel, dressing, and dyeing of fur	69.16	30.84	1,767	53.67	46.33	1,869
19 Leather and leather products	80.02	19.98	936	89.45	10.55	1,175
20 Wood and wood products	55.49	44.51	4,759	72.26	27.74	4,354
21 Pulp, paper, and paper products	33.55	66.45	4,217	74.10	25.90	780
22 Publishing and printing	40.34	59.66	1,688	81.61	18.39	4,025
23 Coke, refined petroleum products and nuclear fuel	-	-	-	58.05	41.95	205
24 Chemicals and chemical products	45.38	54.62	11,581	47.76	52.24	10,017
25 Rubber and plastic products	76.48	23.52	11,279	84.03	15.97	8,864
26 Other non-metallic mineral products	42.31	57.69	8,963	4244	57.56	8,888
27 Basic metals	40.95	59.05	5,963	42.47	57.53	4,919
28 Fabricated metal products	64.97	35.03	23,803	69.56	30.44	23,071
29 Machinery and equipment	53.62	46.38	28,202	57.91	42.09	27,721
30 Electrical and optical equipment	47.52	52.48	909	74.24	25.76	1,277
31 Electrical machinery and apparatus	52.88	47.12	10,265	69.13	30.87	9,047
32 Radio, television, and communication	55.70	44.30	2,684	76.31	23.69	2,533
33 Medical and precision instruments	78.08	21.92	7,760	80.55	19.45	2,714
34 Motor vehicles and trailers	44.36	55.64	6,095	65.81	34.19	5,776
35 Transport equipment	58.43	41.57	2,100	87.50	12.50	1,760
36 Furniture manufacturing	76.86	23.14	5,766	79.55	20.45	7,404
Across all industries	61.30	38.70	162,983	68.19	31.81	147,507

Notes: Table D.3 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.

Appendix E: Trade shocks 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.[25] 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 trade shocks affect the dispersion of labor market power, I run the following regression:

$$\sigma_{jt}^{L} = \gamma_{IMP} IMP_{jt-1}^{CHN} + \gamma_{EXP} EXP_{jt-1}^{CHN} + \upsilon_j + \upsilon_t \,, \tag{E.1}$$

where υ_j and υ_t capture industry and time specific effects. When estimating (E.1) 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) in total imports (exports) flowing from China (instrument group countries) to instrument group countries (China).

Table E.1 shows the associated results from estimating equation (E.1) 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 import competition (export demand) decrease (increase) 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 positive causal relationship between Chinese export demand shocks and the industry level dispersion of firms' labor market power (column 4). This implies that export demand shocks increase inequality in labor market power 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 export demand shocks.

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

TABLE E.1

DISPERSION OF LABOR MARKET POWER AND TRADE SHOCKS

	OLS		IV	
	σ_{jt}^{L}	σ_{jt}^{L}	σ_{jt}^{L}	σ_{jt}^{L}
	(1)	(2)	(3)	(4)
IMP_{jt-1}^{CHN}	-0.0165***	-0.00136	-0.0243***	-0.00196
	(0.00458)	(0.00507)	(0.00639)	(0.00737)
EXP_{jt-1}^{CHN}	0.0592***	0.0108	0.112***	0.126***
	(0.0176)	(0.00849)	(0.0346)	(0.0394)
Time FE	YES	YES	YES	YES
Industry FE	NO	YES	NO	YES
Observations	2,730	2,728	2,730	2,728
R-squared	0.059	0.719	0.032	0.702
First-stage F-test	-	-	10.65	17.15
Number of Industries	231	229	231	229

Notes: Table E.1 reports results from estimating equation (E.1) 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.

Appendix F: Using trade measures based on the BRICS country group

This section shows that all results for the effects of trade shocks 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 $t-1$. The first robustness check underlines the generality of my results with respect to trade shocks from emerging economies. The second check simultaneously addresses concern about splitting the sample into PD- and ND-firms based on the lagged value of the dependent variable and about potential issues resulting from an unclean separation of my sample into PD- and ND-firms. For convenience I only report IV-results for both robustness checks.[26]

TABLE F.1

LABOR MARKET DISTORTIONS AND TRADE SHOCKS FROM 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}	224.00***	-53.41	118.10**	85.12**	229.50*	-207.00**
	(59.50)	(42.23)	(45.21)	(39.12)	(117.20)	(103.70)
EXP_{it-1}^{BRICS}	-264.60***	183.90***	-24.44	21.38	-393.60***	383.40***
	(71.72)	(57.88)	(67.74)	(56.63)	(152.60)	(128.23)
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	108,806	108,806	63,180	63,247	41,301	41,301
R-squared	0.920	0.863	0.832	0.845	0.875	0.887
First-stage F-test	180.60	180.60	58.01	58.01	52.88	52.88
Number of firms	24,313	24,313	16,474	16,474	8,745	8,745

Notes: Table F.1 reports results from estimating equation (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.

Table F.1 shows the results corresponding to the robustness check which uses the BRICS country group as Germanys trade partner. Table F.1 first pools all

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

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 F.1 with Tables 5 and 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 F.2 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 F.2. first reports results for PD-firms (columns 1 and 2) and subsequently shows results for ND-firms (columns 3 and 4).

TABLE F.2

LABOR MARKET DISTORTIONS AND TRADE SHOCKS, 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}	115.60***	115.60***	208.80*	208.80*
	(43.08)	(43.08)	(124.6)	(124.6)
EXP_{it-1}^{BRICS}	49.68	49.68	-666.80***	-666.80***
	(102.9)	(102.9)	(218.00)	(218.00)
Firm $*$ Industry FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Firm level controls	YES	YES	YES	YES
Observations	59,365	59,365	37,825	37,825
R-squared	0.848	0.848	0.891	0.891
First-stage F-test	82.04	82.04	26.78	26.78
Number of firms	15,614	15,614	7,820	7,820

Notes: Table F.2 reports results from estimating equation (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, $\lvert\delta_{it}^L\rvert$. 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.

As consequence of eliminating firms which switched their type, results for δ_{it}^L and $\lvert\delta_{it}^L\rvert$ are identical. Again, comparing Table F.2 with Table 6 of the main text shows that my results are qualitatively unchanged when excluding firms that switched their classification into PD- and ND-firms between the periods t and $t-1$.

REFERENCES (ONLINE APPENDIX)

DE LOECKER, J., AND P. K. GOLDBERG, "Firm performance in a global market," *Annual Review of Economics 6* (2014), 201-227.

DE LOECKER, J., P. K. GOLDBERG, A. K. KHANDELWAL, AND N. PAVCNIK, "Prices, markups, and trade reform," *Econometrica 84* (2016), 445-510.

DOBBELAERE, S. AND K. KIYOTA, "Labor market imperfections, markups and productivity in multinationals and exporters," *Labour Economics (forthcoming).*

DOBBELAERE, S., K. KIYOTA, AND J. MAIRESSE, "Product and labor market imperfections and scale economies: Micro-evidence on France, Japan and the Netherlands," *Journal of Comparative Economics 43* (2015), 290-322.

DOBBELAERE, S., R. LAUTERBACH, AND J. MAIRESSE, "Micro-evidence on product and labor market regime differences between Chile and France," *International Journal of Manpower 37* (2016), 229-252.

DOBBELAERE, S. AND J. MAIRESSE, "Panel data estimates of the production function and product and labor market imperfections," *Journal of Applied Econometrics 28* (2013), 1-46.

Halle Institute for Economic Research –
Member of the Leibniz Association

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

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

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

www.iwh-halle.de

ISSN 2194-2188

Leibniz
Association