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Markup responses to Chinese imports

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Non-technical summary

Research Question

The strong export performance of China has spurred several researchers to investigate the implications of the associated rise in imports for the receiving economies. Besides its consequences for labor markets, studies investigate the effects of Chinese imports on firm performance measures such as productivity and markups.

Contribution

The present paper contributes to this literature by investigating various channels through which Chinese imports may impact markups of Danish firms. In particular, the paper makes a distinction between pro-competitive effects and effects related to international sourcing activities. These two aspects may have opposing effects on firm-level markups. On the one hand, increased competitive pressure may force firms to lower their output prices and thus their markups. On the other hand, a surge in imports from China may result in cheaper inputs for Danish firms, either because these firms directly or indirectly source these inputs from China or because Chinese imports exert pressure on intermediate goods producers in Denmark to lower their output prices. Cheaper inputs imply lower marginal production costs, which may translate into higher markups if cost savings are not fully passed through to consumers. Access to detailed data allows us to investigate these different channels and to decompose effects on markups into price and marginal cost effects. Moreover, the empirical analysis accounts for endogeneity problems by employing an IV strategy which rests on supply-side characteristics of Chinese exports.

Results

The estimation results document that competitive pressure from Chinese imports negatively affects firm-level markups through pressure on output prices. On the other hand, sourcing activities by other firms tend to increase firms' markups due to marginal cost savings associated with intermediate goods imports from China. In contrast, we do not find significant effects from direct offshoring activities.

Nichttechnische Zusammenfassung

Fragestellung

Chinas starke Exportentwicklung hat zu einem erhöhten Interesse an den Folgen für die Einfuhrländer geführt. Neben Auswirkungen auf die Arbeitsmärkte untersuchen Studien die Effekte von chinesischen Importen auf die Entwicklung von Unternehmen, etwa hinsichtlich Produktivität und Markups.

Beitrag

Dieses Papier trägt zu der Literatur bei, indem es verschiedene Kanäle untersucht durch die Einfuhren aus China die Markups von dänischen Firmen beeinflussen können. Hierbei wird zwischen verstärktem Wettbewerb sowie Effekten bezogen auf Offshoring-Aktivitäten unterschieden. Beide Aspekte können gegenläufige Auswirkungen auf Markups von Unternehmen haben. Einerseits kann verstärkter Wettbewerb aufgrund von chinesischen Importen Druck auf die Erzeugerpreise ausüben und damit zu einer Reduktion von Markups führen. Andererseits kann ein Anstieg der Einfuhren aus China günstigere Zwischengüter für dänische Unternehmen bedeuten. So können Firmen diese Güter etwa direkt oder indirekt beziehen. Zudem ist es möglich, dass Einfuhren aus China Preisdruck auf Vorleistungsgüterproduzenten in Dänemark ausüben. Günstigere Zwischengüter bedeuten niedrigere Grenzkosten, die höhere Markups implizieren können, wenn Kosteneinsparungen nicht vollständig an die Verbraucher weitergegeben werden. Detaillierte Daten ermöglichen es, diese verschiedenen Kanäle zu untersuchen und die Auswirkungen auf die Markups in Preis- und Grenzkosteneffekte zu unterscheiden. Darüber hinaus berücksichtigt die empirische Analyse mögliche Endogenitätsprobleme unter Verwendung eines Instrumentenansatzes, der auf angebotsseitigen Aspekten der chinesischen Ausfuhren beruht.

Ergebnisse

Die Schätzergebnisse zeigen, dass sich Wettbewerbsdruck, ausgelöst durch chinesische Einfuhren, negativ auf Markups der Unternehmen auswirkt. Dieses ist durch erhöhten Druck auf die Erzeugerpreise zu erklären. Demgegenüber scheinen Unternehmen von Grenzkosteneinsparungen zu profitieren, die mit Importen chinesischer Zwischengüter anderer Firmen in Verbindung stehen und so die Markups positiv beeinflussen. Im Gegensatz dazu sind die geschätzten Effekte von direktem Offshoring nach China nicht signifikant.

Bundesbank Discussion Paper No 02/2016

Markup Responses to Chinese Imports*

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Abstract

This paper analyzes markup responses of Danish firms to Chinese imports. Besides negative markup responses due to competitive pressure, we present some evidence for marginal cost savings related to Chinese intermediate goods imports which tend to raise firm-level markups.

Keywords: Chinese Imports, Markups

JEL classification: D22, F14, L25.

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1 Introduction

The strong export performance of China has spurred several researchers to investigate the implications of the associated rise in imports for the receiving economies. This paper contributes to this literature by investigating different channels through which Chinese imports may impact markups of Danish firms. In particular, it makes a distinction between pro-competitive effects and effects related to international sourcing activities. These two aspects may have opposing effects on firm-level markups. On the one hand, increased competitive pressure may force firms to lower their output prices and thus their markups. On the other hand, a surge in imports from China may result in cheaper inputs for Danish firms, either because these firms directly or indirectly source these inputs from China or because Chinese imports exert pressure on intermediate goods producers in Denmark to lower their output prices. Cheaper inputs imply lower marginal production costs, which may translate into higher markups if cost savings are not fully passed through to consumers.

Access to detailed data allows us to investigate these different channels and to decompose effects on markups into price and marginal cost effects. The estimation results document that competitive pressure from Chinese imports negatively affects firm-level markups, which can be explained by pressure on output prices. On the other hand, sourcing activities by other firms tend to increase firms' markups due to marginal cost savings associated with Chinese intermediate goods imports. In contrast, we do not find significant effects from direct offshoring activities.

A number of other recent studies investigate the implications of Chinese imports for markups or prices in the sourcing countries. De Loecker, Fuss and Van Biesebroeck (2014) present an analysis which is most closely related to the current paper. They show that sector-level imports from China are associated with lower marginal production costs and output prices of Belgium manufacturing firms and have an overall slightly positive effect on markups. The present paper attempts to dig even deeper into the different mechanisms by constructing firm-specific competition and sourcing variables while accounting for potential endogeneity problems. Firm-specific import variables allow us to factor in that, even within the same narrowly defined sector, firms vary substantially in terms of their exposure to competitive pressure from China. Moreover, we may investigate additional issues, for example, by distinguishing between effects related to direct sourcing and sourcing activities by other firms.

2 Empirical Strategy

2.1 Data and Main Variables

We make use of three data sets available at Statistics Denmark for the period 1997 to 2008. The first two data sets are rather standard in nature, containing detailed information on balance sheets and firms' export and import activities (by product and destination). The third data set is the commodity statistic which provides information on manufacturing firms' sales by product at detailed product level. The data set is based on a survey of firms that employ at least ten individuals or meet a revenue threshold. Moreover, we make use of the BACI data set containing bilateral trade flows by product category at the HS6-digit level.

We identify the different channels through which Chinese imports may affect firm-level markups by employing three distinct variables. Ashournia, Munch and Nguyen (2014), who investigate the impact of Chinese imports on wages in Denmark, find that, even within narrowly defined industries, firms vary widely in their exposure to import competition from China, which emphasizes the need for a firm-specific competition measure. We thus compute an import competition proxy as

$$IC_{it}^{cn} = \sum_{k \in \Omega_i} s_{ik} \frac{M_{kt}^{cn} - M_{ikt}^{cn}}{M_{kt} - M_{ikt} + T_{kt}}.$$

M_{kt}^{cn} are Danish imports of product k (measured at the HS6-digit level) in year t from China, M_{ikt}^{cn} are imports of that product from China by firm i, M_{kt} are total Danish imports of product k, M_{ikt} are total imports of this product by firm i, and T_{kt} are total sales of product k by firms in Denmark in that year. To obtain a firm-specific competition variable, we take the weighted average of this penetration measure in the set of firm i's products Ω_i. We define the weights s_{ik} as the share of product k in firm i's set of products during the pre-sample period. We use the years 1997 and 1998 as the pre-sample period[1] and keep s_{ik} constant during the sample period.

The other two import variables account for international sourcing of intermediate goods. First, we measure firm-level offshoring to China (OFF_{it}^{cn}) as the share of intermediate goods imports from China in a firm's total sales ($M_{it}^{cn,I}/T_{it}$).[2] Second, we control for offshoring activities of other firms by computing a penetration measure at the HS-section level d and relate each firm to one HS-section according to its main product:

$$OFF_{dt}^{cn} = \frac{M_{dt}^{cn,I} - M_{idt}^{cn,I}}{M_{dt}^{I} - M_{idt}^{I} + T_{dt}^{I}}.$$

Besides importing variables, we require estimates of firm-level markups. To this end, we use the methodology of De Loecker and Warzynski (2012), which relies on the fairly modest assumptions of cost-minimizing firms and the presence of at least one variable input that is free of adjustment costs. Firm-level markups μ_{it} may then be computed from the ratio of the output elasticity of the variable input and its cost share in a firm's output. While the latter term is directly observable in our data, we follow De Loecker and Warzynski and obtain the output elasticity by estimating a translog value added production. Due to Denmark's highly flexible labor market, we consider labor as the variable input that is free of adjustment costs. Note that the production function estimation also provides us with an estimate of total factor productivity (TFP).

Finally, we use information on unit values available at detailed product level in the commodity statistic and compute a firm-specific price index. The price index is of interest since it allows us to decompose markup responses into price and marginal cost components. However, we note that this price proxy is rather crude e.g. because unit value data are

[1] We allow firms to enter the sample after 1997 and consider their first year of appearance as belonging to the pre-sample period.

[2] Superscript I stands for intermediate goods which are identified based on the BEC classification.

known to be noisy. In a supplementary appendix we document how we clean these data and present more details on data sources, markup and price index computations as well as descriptive statistics and some robustness checks.

2.2 Econometric Approach

We use the following specification to analyze markup responses to Chinese imports

$$\ln(\mu_{it}) = \beta_1 IC^{cn}_{it-1} + \beta_2 OFF^{cn}_{dt-1} + \beta_3 OFF^{cn}_{it-1} + \lambda x_{it-1} + \gamma_i + \gamma_d + \gamma_t + \nu_{it},$$

where x_{it-1} is a vector of firm-level control variables lagged by one year to alleviate endogeneity concerns, ν_{it} is an error term, and γ_i, γ_d and γ_t are firm, HS-section, and year fixed effects. Note that we also lag the import variables, since firms may take some time before adjusting their markups to changes in their operating environment.

We account for endogeneity concerns regarding the import variables employing an IV approach which is based on Chinese exports to countries other than Denmark in order to instrument for Denmark's imports from China. The IV strategy rests on the idea that China's export growth is largely associated with supply side factors, for example, related to improvements in Chinese firms' competitiveness. Dauth, Findeisen and Suedekum (2014) provide a recent application of this strategy emphasizing that the choice of the set of "other countries" is important in order to have a convincing IV approach. We follow their argumentation and include in this set non-EMU and non-neighboring western high-income countries except for the US.[3] The supplementary appendix presents further details about the IV strategy.

3 Results

Table 1 contains the estimation results. We begin with OLS estimations where we include the import variables separately one at a time. The firm-specific import competition measure enters the regression equation with a negative and highly significant coefficient (column i), implying that increased competitive pressure from China is, on average, associated with a decrease in firm-level markups. In column (ii) we observe that the aggregated measure of intermediate goods sourcing from China of other firms exhibits a positive and weakly significant effect on firm-level markups. Hence, these imports appear to be associated with marginal cost savings which are not fully passed through to consumers and thus translate into higher markups; a mechanism which is in line with heterogenous firms models featuring a demand elasticity increasing in price. As suggested above, the variable may pick up indirect sourcing activities and effects related to competitive pressure on intermediate goods producers in Denmark. We next include the firm-level offshoring variable in column (iii) which is, however, estimated imprecisely and thus does not exert a significant effect on markups. The insignificant coefficient may, for example, also be related to certain costs associated with direct offshoring to China, which are reduced only over time when a firm becomes better accustomed to this sourcing channel.

[3] The set of countries includes Australia, Canada, Great Britain, New Zealand, Norway, and Switzerland.

Interestingly, adding all three variables simultaneously to the regression (column iv) reinforces the effects found in columns (i) and (ii), indicating that these variables indeed do measure alternative aspects. In column (v) we further check whether our interpretation of the effects of IC_{it}^{cn} and OFF_{dt}^{cn} is sensible. Specifically, we use the price index as dependent variable and find that an increase in IC_{it}^{cn} is associated with a reduction in output prices. Moreover, since $\ln(\text{MC}) = \ln(\text{PI}) - \ln(\mu)$, we can infer that OFF_{dt}^{cn} tends to lower marginal costs (by -0.935).[4]

Table 1: Results

	i	ii	iii	iv	v	vi	vii
	$\ln(\mu)$ OLS	$\ln(\mu)$ OLS	$\ln(\mu)$ OLS	$\ln(\mu)$ OLS	ln(PI) OLS	$\ln(\mu)$ OLS	$\ln(\mu)$ IV
IC_{it-1}^{cn}	-0.512***			-0.573***	-0.448**	-0.526***	-1.086***
	(0.148)			(0.147)	(0.201)	(0.129)	(0.329)
$OFF_{dt-1}^{cn,I}$		0.392*		0.580**	-0.355	0.439**	1.598**
		(0.204)		(0.226)	(0.368)	(0.186)	(0.710)
$OFF_{it-1}^{cn,I}$			0.271	0.296	0.177	0.245	0.807
			(0.274)	(0.278)	(0.425)	(0.236)	(1.198)
$\ln(\text{wage}_{it-1})$						-0.144***	-0.144***
						(0.021)	(0.021)
$\ln(\text{assets}_{it-1})$						-0.006	-0.008
						(0.009)	(0.009)
ω_{it-1}						0.214***	0.212***
						(0.016)	(0.016)
Observations	18,971	18,971	18,971	18,971	18,971	18,971	18,971
R2	0.025	0.023	0.023	0.025	0.147	0.063	0.037
F, IC_{it-1}^{cn}							105.981
F, $OFF_{dt-1}^{cn,I}$							129.499
F, $OFF_{it-1}^{cn,I}$							11.693

Clustered (firm-level) standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Regressions contain firm, HS-section, and year fixed effects.

In column (vi) we add a series of control variables to the markup regression, namely the average wage, TFP (ω_{it}), and the firms' total assets. Compared to column (iv), the coefficients on IC_{it}^{cn} and OFF_{dt}^{cn} are hardly affected. Further note that, as expected, we find that an increase in wages - and thus higher marginal production costs - implies lower markups, while an increase in productivity is associated with higher markups. Finally, in column (vi) we account for the endogeneity of the import variables employing our IV strategy. The F-tests of excluded instruments indicate that this strategy performs well. Qualitatively, the earlier results are confirmed, while the coefficient magnitudes increase somewhat. Considering that, during the sample period, the average value across firms of IC_{it}^{cn} steadily increased from 0.008 to 0.023 and the average value of OFF_{dt}^{cn} from 0.009 to 0.024, the coefficient magnitudes imply that markups decreased on average by 1.6% due to competition effects, while they tended to increase by 2.4% due to marginal cost savings.

[4]This effect is also statistically significant.

4 Conclusion

Based on detailed micro-data, this paper analyzes different channels through Chinese imports may impact markups of Danish firms. Besides negative markup responses due to competitive pressure, we present some evidence for marginal cost savings related to Chinese intermediate goods imports which tend to raise firm-level markups.

A Appendix

This appendix contains additional details about the data, markup and price index computations, the IV strategy as well as descriptive statistics and some robustness checks.

A.1 Data

In the paper we make use of three distinct data sets available at Statistics Denmark for the period 1997 to 2008. First, we use the data set *FIRE* ("Regnskabsstatistik") which contains detailed firm-level balance sheet information. This data set provides us with key variables for computing firm-level markups and productivity, namely value added, capital stock, number of employees, wages and salaries, and materials. We retain all firms with information on the relevant variables. We clean these data first by dropping observations with implausible values[5] and then trimming extreme values in terms of three ratios, namely value added per employee, value added per capital employed, and valued added per wages paid by dropping the first and last percentiles (computed within industries and years) in the distribution of these variables.

All variables in *FIRE* are presented in nominal values. We make use of different deflators for the respective variables. First, we follow Eslava, Haltiwanger, Kugler and Kugler (2004) quite closely in generating a real capital stock series K_{it} from

$$K_{it} = (1-\delta)K_{it-1}\frac{I_{it}}{D_t},$$

where K_{it} is firm i's capital stock, δ is the depreciation rate which equals 0.05, D_t is a deflator for capital goods, and I_{it} are firm i's gross investments computed from yearly changes in the book values of firms' total fixed assets and reported depreciation ($I_{it} = K_{it} - K_{it-1} + d_{it}$). The capital stock series is initialized in the year a firm enters the sample by deflating the book value of total fixed assets with $(D_t + D_{t-1})/2$. Second, we deflate materials, wages, and value added using an intermediate goods price index, the CPI, and an industry-specific price index available at the NACE 2-digit level, respectively.

The second data set applied in this paper is the commodity statistic *VARS* ("Industriens salg af varer"), which provides information on manufacturing firms' sales by product at the 10-digit CN level on a quarterly basis. The commodity statistic is a survey of sales by product of firms that employ at least ten individuals or meet a revenue threshold. The data set covers roughly one-third of all manufacturing firms in Denmark, which account for about 90% of total sales in the manufacturing sector. The data contain information

[5] We drop observations with non-positive values for turnover, fixed capital stock, materials, total assets, wage bill, or value added.

on both the value and the volume of transactions. The data set is essential for computing firm-level measures of import competition and it allows us to construct a firm-level price index from unit values as outlined below.

The third data set from Statistics Denmark used in this paper is called *UHDI* ("Udenrigshandel diskretioneret"). This contains customs data about exports and imports of firms (by product and destination) active in Denmark during the sample period. The data come from two sources: Intrastat (for trade among EU member states) and Extrastat (for trade to a country outside the EU). Extrastat export data are derived from custom forms and tax authorities and cover nearly all trade, while Intrastat export data are self-reported figures by Danish firms that exceed certain export and import thresholds pursuant to the EU regulation.[6] This data set is used to generate the import variables described in the paper. The import competition measure is computed at the HS6-digit level concorded over time following Van Beveren, Bernard, and Vandenbussche (2012). The three data sets from Denmark Statistics can be merged using a unique firm identifier. Note that we keep only manufacturing firms (NACE rev.1.1 codes 15-37) with at least ten employees that are in the sample for at least three years.

Finally, we make use of the BACI data set (Gaulier and Zignago, 2010), which contains information on bilateral trade flows by product category at the HS6-digit level. The data are used to generate our instruments as described below.

A.2 Empirical Methodology

This section presents the empirical strategy for estimating firm-level markups and total factor productivity as well as the construction of the firm-level price index.

A.2.1 Firm-level Markups

We follow the methodology of De Loecker and Warzynski (2012) for estimating firm-level markups. The strategy builds on insights from Hall (1988) and relies on fairly modest assumptions; specifically, the approach rests on the assumptions of cost-minimizing firms and the presence of at least one variable input that is free of adjustment costs. The methodology does not depend on a particular type of competition or functional form of demand and it accommodates a variety of (static) price-setting models.

First, note that cost minimization implies that optimal input demand is satisfied when a firm equalizes the output elasticity of any variable input to its input costs share:

$$\frac{P_{it}^X X_{it}}{\lambda_{it} Q_{it}} = \frac{\partial Q_{it}}{\partial X_{it}} \frac{X_{it}}{Q_{it}}, \tag{1}$$

where X_{it} is the choice of input X by firm i in year t, P_{it}^X is the price of that input, λ_{it} are marginal production costs and Q_{it} is the total output of the firm. The right-hand side of equation (1) represents the output elasticity of the input X, which we denote ε_{it}^X. Defining the markup as the price-marginal cost ratio ($\mu_{it} = \frac{P_{it}}{\lambda_{it}}$) and rearranging (1) yields

[6] For instance, in 2002 the thresholds were DKK 2.5 million for exports and DKK 1.5 million for imports. The thresholds are set each year separately for imports and exports in order to ensure coverage of 95% and 97% for imports and exports, respectively.

$$\mu_{it}\frac{P^X_{it}X_{it}}{P_{it}Q_{it}} = \varepsilon^X_{it}. \tag{2}$$

Perfect competition would imply that prices equal marginal costs such that the revenue share equals the output elasticity of input X. However, in the case of imperfect competition, revenue shares are typically lower than output elasticities which means that a firm's markup can be recovered from

$$\mu_{it} = \frac{\varepsilon^X_{it}}{\alpha^X_{it}} \tag{3}$$

with $\alpha^X_{it} = \frac{P^X_{it}X_{it}}{P_{it}Q_{it}}$. Since α_{it} is directly observable in most firm-level data sets, all that is needed to obtain μ_{it} is an estimate of ε^X_{it}. We follow De Loecker and Warzynski (2012) in the empirical implementation and obtain ε^X_{it} by estimating a value added production function and using the output elasticity of labor to recover firm-level markups. Given the highly flexible labor market in Denmark, it appears reasonable to consider labor as the variable input that is free of adjustment costs. In the following subsection we briefly outline the estimation of the output elasticity.

A.2.2 Estimating Output Elasticities

We use a translog production function to estimate the output elasticities. As noted by De Loecker and Warzynski, this production function is preferred in the current setup, since Cobb-Douglas production functions restrict the output elasticities to being constant across firms within similar sectors, which implies that variation in technology across firms is attributed to variation in markups which potentially biases the estimation results. As standard in the literature, we assume that technological progress is Hicks-neutral such that the value added translog production function is given by

$$y_{it} = \alpha_l l_{it} + \alpha_{ll} l^2_{it} + \alpha_k k_{it} + \alpha_{kk} k^2_{it} + \alpha_{lk} l_{it} k_{it} + \omega_{it} + \epsilon_{it}, \tag{4}$$

where all variables in equation (4) are presented in lower-case letters which indicate logs. y_{it} represents value added (deflated by a sector-specific deflator) of firm i in year t, l_{it} and k_{it} are firm-level inputs of labor and capital, ω_{it} is a measure of unobserved (by the econometrican, and observed by the manager) firm-level productivity that captures a constant term and ϵ_{it} is noise (capturing measurement error and unanticipated shocks to output). Note that a Cobb-Douglas production function is nested in equation (4) and obtained when dropping the higher-order and interaction terms.

Estimating equation (4) imposes the challenge of controlling for unobserved productivity shocks which are potentially correlated with input choices and may thus lead to inconsistent estimates of the production function. As commonly done in the literature, we use a control function approach to deal with this simultaneity problem. Specifically, we follow the insights by Ackerberg, Caves and Frazer (2006) – henceforth ACF – while relying on material inputs to proxy for unobserved productivity, as suggested by Levinsohn and Petrin (2003). The important point to note is that a firm's choice of materials is directly related to its productivity, capital stock, and labor inputs. The material demand equation is given by $m_{it} = m_t(k_{it}, l_{it}, \omega_{it})$ and an expression for productivity in terms of observables is obtained by inverting this equation. Substituting the resulting expression

($\omega_{it} = h_t(k_{it}, l_{it}, m_{it})$) into equation (4) yields the estimation equation for the first step of the algorithm:

$$y_{it} = \phi_t(k_{it}, l_{it}, m_{it}) + \epsilon_{it}, \tag{5}$$

where $\phi_t(\cdot) = \alpha_l l_{it} + \alpha_{ll} l_{it}^2 + \alpha_k k_{it} + \alpha_{kk} k_{it}^2 + \alpha_{lk} l_{it} k_{it} + h_t(k_{it}, l_{it}, m_{it})$ and the function $h_t(\cdot)$ is approximated using a third-order polynomial expansion of its argument. Hence, the first step provides us with estimates of $\hat{\phi}_t(\cdot)$ and ϵ_{it} and allows computing productivity for any parameter value $\alpha = (\alpha_l, \alpha_{ll}, \alpha_k, \alpha_{kk}, \alpha_{lk})$ as $\omega(\alpha) = \hat{\phi} - (\alpha_l l_{it} + \alpha_{ll} l_{it}^2 + \alpha_k k_{it} + \alpha_{kk} k_{it}^2 + \alpha_{lk} l_{it} k_{it})$. The second stage then relies on the law of motion of productivity which is modeled as a first-order Markov process:

$$\omega_{it} = g(\omega_{it-1}) + \upsilon_{it}. \tag{6}$$

$g(\cdot)$ is some polynomial function; in the application in this paper it is a third-order polynomial. We can then obtain the innovation to productivity given α ($\upsilon_{it}(\alpha)$) as the residual from non-parametrically regressing $\omega_{it}(\alpha)$ on its lag ($\omega_{it-1}(\alpha)$). Next, we can specify moments to identify the parameters of interest ($E[\upsilon_{it}(\alpha) d_{it}] = 0$) and minimize the sample analog by GMM.[7] We estimate the production function separately by NACE rev. 1.1 subsection which amounts to 12 different sector aggregates.[8] With the estimated production function parameters at hand, the output elasticity of labor is computed as $\hat{\varepsilon}_{it}^L = \hat{\alpha}_l + 2\hat{\alpha}_{ll} l_{it} + \hat{\alpha}_{lk} k_{it}$.

Even though we are primarily interested in the labor coefficient, estimation of the capital coefficient is relevant, since it allows us to compute total factor productivity which is obtained as a residual.

A.2.3 Computing a Firm-level Price Index

As noted in the main text, we compute a firm-specific price index in order to investigate price responses to Chinese imports. The price index P_{it} is computed as a Törnqvist index which gives the weighted average of the growth in unit values of all products k produced by firm i in years t and $t-1$ (Eslava et al., 2004; Smeets and Warzynski, 2013):

$$\Delta P_{it} = \sum_{k=1}^{K} \bar{h}_{kit} \Delta \ln(P_{kit}),$$

where $\Delta \ln(P_{kit}) = \ln(P_{kit}) - \ln(P_{kit-1})$, $\bar{h}_{kit} = \frac{h_{kit} + h_{kit-1}}{2}$, P_{kit} is the price of product k charged by firm i in year t and h_{kit} is the share of product k in firm i's total sales in year t.[9] We take 1999 as the base year ($P_{i,1999} = 100$) and then add the computed firm-level

[7] In the case of the value-added translog production function, the set of instruments is $d_{it} = l_{it-1}, k_{it}, l_{it-1}^2, k_{it}^2, l_{it-1} k_{it}$.

[8] Note that when estimating the production function, we aggregate the subsections DB (manufacture of textiles and textile products) and DC (manufacture of leather and leather products), since DC contains only a very small number of firms.

[9] The product-level k here is the CN8-digit level concorded over time following Van Beveren et al. (2012).

price change to the index:[10]

$$\ln P_{it} = \ln P_{it-1} + \Delta P_{it}$$

for $t > 1999$. The price levels are obtained by taking the exponential of the natural log of prices $\ln P_{it}$.

We note two caveats with respect to the unit value data used to compute the price index. First, as found in many data sets of this kind (see, for example, Eslava et al., 2004; Kugler and Verhoogen, 2012), unit values of products computed at detailed product-level are noisy and may change substantially from one year to another. We therefore preform a three-step cleaning procedure where the first two steps are in line with the approach chosen by Kugler and Verhoogen (2012).[11] First, we winsorize changes in log unit values at the CN8-digit level at the 3rd and 97th percentiles within product codes. Second, since there are a number of huge price changes remaining in the data, we also winsorize observations that deviate by more than the mean plus/minus five times the standard deviation computed on a yearly basis. Third, we winsorize the first and last percentiles of the resulting firm-level price deflator on a yearly basis.

The second caveat is that quantity information necessary for computing the unit values is quite frequently lacking. We deal with this issue by imputing missing growth rates of unit values at CN8-product levels using data on unit values by product publicly available from Statistics Denmark's website. Given the level of disaggregation of CN8-product codes, we believe that using changes of the weighted average of unit value at the CN8-product-level published by Statistics Denmark is a reasonable approach for imputation.[12] Using this approach, we impute data for more that 6,000 firm-product-year observations out of around 28,000 missings. Finally, for firms in our data for which we cannot compute the price index due to missing quantity information, we follow Eslava et al. (2004) and Smeets and Warzynski (2013) and use the average price charged in the NACE 4-digit sector of the firm.

A.2.4 IV strategy

As mentioned in the main text, our OLS estimations may suffer from endogeneity; for instance, there may be unobserved technology shocks which influence both markups and product-level imports from China. We therefore use an IV approach which is similar to the strategy proposed by Autor, Dorn, and Hanson (2013) and Ashournia et al. (2014). The IV strategy rests on the fact that China's export growth is largely associated with supply side factors related to improvements in Chinese manufacturing firms' competitiveness, the reduction of China's trade barriers and its accession to the WTO. Hence, China's exports to other countries may be used to instrument for China's exports to Denmark. Dauth et al. (2014) investigate local labor market effects from Chinese imports in Germany using a strategy similar to that of Autor et al. (2013). Dauth et al. (2014) point out

[10]In line with Smeets and Warzynski (2013), we deal with firms entering the sample after the base year 1999 by computing the industry average price for the first year of their appearance and then following a similar procedure as described above.

[11]Note that we depart from Kugler and Verhoogen (2012) in that we base the data cleaning on yearly changes in unit values rather than the level of unit values.

[12]Note that we also apply the first two steps of the cleaning procedure described above to these data in order to account for a few large outliers, while we compute the percentiles by year instead of within product codes during the first step.

that the set of "other countries" is important in order to have a convincing IV approach. Specifically, the authors emphasize that the instrument needs to fulfill three criteria. First, it should have explanatory power meaning that Chinese exports to the other countries need to be correlated with Chinese exports to Denmark. Second, there should not be a strong correlation between unobservable supply and demand shocks in the other countries and those in Denmark, since, otherwise, the instrument does not fulfill its purpose of purging Chinese exports to Denmark from exactly these shocks. Third, Chinese exports to the other countries should have no independent effects on firms in Denmark other than through the exogenous rise of China.

For these reasons, we focus on the group of non-EMU and non-neighboring western high-income countries except for the US.[13] Chinese exports to high-income western economies are highly correlated with those to Denmark. We exclude countries that share a common border with Denmark (Sweden and Germany) from the group of "other countries", since demand and supply shocks in these countries are likely to be correlated with those in Denmark. For similar reasons, we exclude euro area countries since Denmark is highly integrated with these countries due the single market and a fixed exchange rate system. Finally, we also follow Dauth et al. (2014) and exclude the US from the group of "other countries" due to its profound importance in international trade. The instrument is then computed as

$$IVIC_{it}^{cn} = \sum_{k \in \Omega_i} s_{ik} \frac{HICES_{kt}^{cn}}{HICES_{kt}}. \tag{7}$$

$HICES_{kt}^{cn}$ is China's export supply of product k in year t to the group of western high-income countries which is normalized by total exports of product k to these countries ($HICES_{kt}$). This fraction is then weighted by pre-sample shares in order to aggregate it to the firm level. We compute the corresponding instrument for OFF_{dt}^{cn} accordingly at the HS-section level d and relate it to the each firm according to the firm's main HS-section. Moreover, we use the same type of instrument in order to account for endogeneity concerns regarding OFF_{it}^{cn}. To aggregate this variable to the firm-level, we use firm-product-level import shares as weights. Since a firm's import behavior evolves considerably over time, we follow Mion and Zhu (2013) and use the one-year lagged shares as the weight and set this share to zero in case a firm is not importing from China:

$$IVOFF_{it}^{cn} = \sum_{k \in K^{cn,I}} \frac{M_{ikt-1}^{cn,I}}{M_{it-1}^{cnI}} \frac{HICES_{kt}^{cn}}{HICES_{kt}}. \tag{8}$$

A.3 Descriptive Statistics

Table A.1 presents median estimated output elasticities and median markups by industry. Median markups are estimated to amount to 1.23 while varying considerable across sectors. Table A.2 presents distributions of our main variables. First of all, the distribution of markups suggests that markups also vary substantially across firms. Moreover, Table A.2 shows that, while the median values of the firm- and sector-level price indices

[13]The set of countries includes Australia, Canada, Great Britain, New Zealand, Norway, and Switzerland. Note that Dauth et al. (2014) also included Japan and Singapore in the group of "other countries". In our case, the instrument performs better when excluding these countries which is why we decided to focus on western high-income countries.

are quite similar, the firm-level price index exhibits a lot more variation. Furthermore, we can observe that firms vary substantially in their exposure to Chinese imports; while some compete heavily with Chinese imports, other firms are completely exempted from competitive pressure reinforcing the relevance of a firm-specific competition measure.

Table A.1: Median Output Elasticities and Markups

	Obs.	ε_{it}^{l}	ε_{it}^{k}	μ
Food, beverages, tobacco (DA)	1,604	0.740	0.259	1.150
Textiles, textile products, leather (DB DC)	829	0.856	0.124	1.237
Wood (DD)	1,031	0.910	0.141	1.270
Pulp, paper, publishing, printing (DE)	2,138	0.821	0.201	1.179
Chemicals and man-made fibres (DG)	624	0.783	0.175	1.242
Rubber, plastic (DH)	1,324	0.763	0.228	1.163
Other non-metallic mineral prod. (DI)	886	0.831	0.217	1.266
Basic and fabricated metal (DJ)	3,045	0.909	0.118	1.272
Machinery and equipment (DK)	3,406	0.869	0.128	1.190
Electrical and optical equipment (DL)	1,821	0.892	0.107	1.271
Transport equipment (DM)	506	0.893	0.142	1.258
Furniture, recycling (DN)	1,757	0.950	0.138	1.315
Total	18,971			1.229

Table A.2: Distributions of Main Variables

	mean	sd	p5	p10	p25	p50	p75	p90	p95
μ_{it}	1.27	0.36	0.82	0.93	1.08	1.23	1.41	1.66	1.87
PI_{it}	126.6	73.1	59.0	76.4	97.1	110.4	133.0	184.0	232.4
PI_{dt}	110.1	8.4	100.9	101.6	104.0	107.8	114.0	120.6	126.1
IC_{it}^{cn}	0.015	0.037	0.000	0.000	0.000	0.002	0.010	0.041	0.080
$OFF_{dt}^{cn,I}$	0.017	0.025	0.001	0.002	0.007	0.011	0.021	0.031	0.060
$OFF_{it}^{cn,I}$	0.002	0.013	0.000	0.000	0.000	0.000	0.000	0.001	0.007
Number of observations: 18,971									

A.4 Robustness

In this section we perform a number of robustness checks. First, we re-estimate the production function while allowing a firm's input demand to depend on the variables capturing Chinese imports; i.e.

$$m_{it} = m_t(k_{it}, l_{it}, \omega_{it}, IC_{it}^{cn}, OFF_{it}^{cn}, OFF_{dt}^{cn}).$$

We refer to this robustness check as *Adjusted I* in the tables below. Second, we additionally adjust the input share for potential measurement error and unanticipated shocks to production, as suggested by De Loecker and Warzynski (2012); specifically, we compute the input share as

$$\frac{P_{it}^{X} X_{it}}{P_{it} \frac{Q_{it}}{exp(\epsilon_{it})}},$$

where ϵ_{it} is obtained from equation 5. We call this robustness check *Adjusted II* in the results tables below.

Besides changing the specification of the ACF estimation algorithm and adjusting the input cost share, we also use alternative approaches for estimating the production function. First, we use a GMM-type version of Olley and Pakes (1996) – henceforth OP – as described in ACF. Second, we estimate the production function using pooled OLS and firm fixed effects, respectively. We run these robustness checks using our OLS as well a IV strategy for the main model presented in the paper with markups as the dependent variable.

Table A.3 presents the robustness checks for the ACF approach to estimate the production function used in the paper. Columns (i) and (ii) contain results presented in the paper to make comparison easier. The results in the remaining columns (iii) to (vi) suggest that the findings are not very sensitive to the described changes. The coefficients of IC^{cn}_{it-1} and $OFF^{cn,I}_{dt-1}$ are always significant; in most cases at least at the 5%-level. A similar statement can be made with respect to the robustness checks involving the GMM-OP approach to estimate the production function presented in Table A.4; i.e. the coefficients of IC^{cn}_{it-1} and $OFF^{cn,I}_{dt-1}$ are always significant, at least at the 5%-level. Finally, results based on pooled OLS estimation of the production function presented in Table A.5 suggest that the results are qualitatively similar. A fixed effect estimation approach of the production function leads a smaller coefficient of $OFF^{cn,I}_{dt-1}$, while it is statistically significant at the 10%-level in the case of IV estimations.

Table A.3: Robustness - ACF Estimation Approach for Production Function

	i	ii	iii	iv	v	vi
	Basline		*Adjusted I*		*Adjusted II*	
	OLS	IV	OLS	IV	OLS	IV
IC^{cn}_{it-1}	-0.526***	-1.086***	-0.531***	-1.116***	-0.232**	-0.557*
	(0.129)	(0.329)	(0.128)	(0.330)	(0.116)	(0.325)
$OFF^{cn,I}_{dt-1}$	0.439**	1.598**	0.415**	1.618**	0.556**	1.983**
	(0.186)	(0.710)	(0.182)	(0.716)	(0.265)	(0.958)
$OFF^{cn,I}_{it-1}$	0.245	0.807	0.234	0.771	0.139	-0.049
	(0.236)	(1.198)	(0.237)	(1.203)	(0.233)	(1.330)
$\ln(\text{wage}_{it-1})$	-0.144***	-0.144***	-0.145***	-0.145***	-0.106***	-0.106***
	(0.021)	(0.021)	(0.021)	(0.021)	(0.017)	(0.017)
$\ln(\text{assets}_{it-1})$	-0.006	-0.008	-0.006	-0.008	0.005	0.004
	(0.009)	(0.009)	(0.009)	(0.009)	(0.006)	(0.006)
ω_{it-1}	0.214***	0.212***	0.213***	0.211***	0.056***	0.054***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.011)	(0.011)
Observations	18,971	18,971	18,971	18,971	18,971	18,971
R2	0.063	0.037	0.061	0.036	0.032	0.002
F, IC^{cn}_{it-1}		105.981		105.964		105.964
F, $OFF^{cn,I}_{dt-1}$		129.499		129.549		129.549
F, $OFF^{cn,I}_{it-1}$		11.693		11.695		11.695

Clustered (firm-level) standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table A.4: Robustness - OP-GMM Estimation Approach for Production Function

	i	ii	iii	iv	v	vi
	Basline		*Adjusted I*		*Adjusted II*	
	OLS	IV	OLS	IV	OLS	IV
IC^{cn}_{it-1}	-0.515***	-0.995***	-0.519***	-1.003***	-0.362**	-0.962***
	(0.133)	(0.323)	(0.133)	(0.323)	(0.145)	(0.328)
$OFF^{cn,I}_{dt-1}$	0.467**	1.459**	0.460**	1.453**	1.220***	3.025***
	(0.203)	(0.648)	(0.201)	(0.646)	(0.304)	(0.723)
$OFF^{cn,I}_{it-1}$	0.239	0.762	0.236	0.761	0.038	0.558
	(0.228)	(1.166)	(0.227)	(1.164)	(0.252)	(1.261)
ln(wage_{it-1})	-0.157***	-0.157***	-0.157***	-0.156***	-0.120***	-0.118***
	(0.021)	(0.021)	(0.021)	(0.021)	(0.019)	(0.020)
ln(assets_{it-1})	-0.007	-0.009	-0.006	-0.008	0.007	0.005
	(0.009)	(0.009)	(0.009)	(0.009)	(0.007)	(0.007)
ω_{it-1}	0.217***	0.215***	0.215***	0.214***	0.042***	0.038***
	(0.016)	(0.016)	(0.017)	(0.017)	(0.012)	(0.012)
Observations	17,634	17,634	17,634	17,634	15,322	15,322
R2	0.068	0.040	0.066	0.039	0.029	0.002
F, IC^{cn}_{it-1}		108.690		108.696		117.649
F, $OFF^{cn,I}_{dt-1}$		146.830		146.822		133.906
F, $OFF^{cn,I}_{it-1}$		10.266		10.265		9.977

Clustered (firm-level) standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table A.5: Robustness - OLS and Fixed Effects (FE) Estimations of Production Function

	i	ii	iii	iv
	OLS Basline		*FE Baseline*	
	OLS	IV	OLS	IV
IC^{cn}_{it-1}	-0.525***	-1.074***	-0.554***	-1.301***
	(0.129)	(0.329)	(0.132)	(0.331)
$OFF^{cn,I}_{dt-1}$	0.455**	1.620**	0.148	1.274*
	(0.188)	(0.715)	(0.173)	(0.662)
$OFF^{cn,I}_{it-1}$	0.243	0.817	0.200	1.277
	(0.237)	(1.216)	(0.256)	(1.366)
ln(wage_{it-1})	-0.143***	-0.143***	-0.120***	-0.120***
	(0.021)	(0.021)	(0.021)	(0.021)
ln(assets_{it-1})	-0.007	-0.009	-0.004	-0.007
	(0.009)	(0.009)	(0.009)	(0.009)
ω_{it-1}	0.214***	0.211***	0.200***	0.198***
	(0.016)	(0.016)	(0.016)	(0.016)
Observations	18,971	18,971	18,971	18,971
R2	0.064	0.037	0.043	0.029
F, IC^{cn}_{it-1}		105.960		106.008
F, $OFF^{cn,I}_{dt-1}$		129.664		130.056
F, $OFF^{cn,I}_{it-1}$		11.696		11.691

Clustered (firm-level) standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

References

Ackerberg, D., K. Caves, and G. Frazer (2006). Structural identification of production functions. MPRA Paper 38349, University Library of Munich, Germany.

Ashournia, D., J. Munch, and D. Nguyen (2014). The Impact of Chinese Import Penetration on Danish Firms and Workers. Economics Series Working Papers 703, University of Oxford, Department of Economics.

Autor, D. H., D. Dorn, and G. H. Hanson (2013). The China Syndrome: Local Labor Market Effects of Import Competition in the United States. *American Economic Review 103*(6), 2121–68.

Dauth, W., S. Findeisen, and J. Suedekum (2014). The Rise Of The East And The Far East: German Labor Markets And Trade Integration. *Journal of the European Economic Association 12*(6), 1643–1675.

De Loecker, J., C. Fuss, and J. Van Biesebroeck (2014). International competition and firm performance : Evidence from Belgium. Working Paper Research 269, National Bank of Belgium.

De Loecker, J. and F. Warzynski (2012). Markups and Firm-Level Export Status. *American Economic Review 102*(6), 2437–71.

Eslava, M., J. Haltiwanger, A. Kugler, and M. Kugler (2004). The effects of structural reforms on productivity and profitability enhancing reallocation: evidence from Colombia. *Journal of Development Economics 75*(2), 333–371.

Gaulier, G. and S. Zignago (2010). BACI: International Trade Database at the Product-Level. The 1994-2007 Version. Working Papers 2010-23, CEPII research center.

Hall, R. E. (1988). The Relation between Price and Marginal Cost in U.S. Industry. *Journal of Political Economy 96*(5), 921–47.

Kugler, M. and E. Verhoogen (2012). Prices, Plant Size, and Product Quality. *Review of Economic Studies 79*(1), 307–339.

Levinsohn, J. and A. Petrin (2003). Estimating Production Functions Using Inputs to Control for Unobservables. *Review of Economic Studies 70*(2), 317–341.

Mion, G. and L. Zhu (2013). Import competition from and offshoring to China: A curse or blessing for firms? *Journal of International Economics 89*(1), 202–215.

Olley, G. S. and A. Pakes (1996). The Dynamics of Productivity in the Telecommunications Equipment Industry. *Econometrica 64*(6), 1263–97.

Smeets, V. and F. Warzynski (2013). Estimating productivity with multi-product firms, pricing heterogeneity and the role of international trade. *Journal of International Economics 90*(2), 237–244.

Van Beveren, I., A. B. Bernard, and H. Vandenbussche (2012). Concording EU Trade and Production Data over Time. NBER Working Papers 18604, National Bureau of Economic Research, Inc.