A Short Note on Trade Shock and Aggregate Productivity*

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Abstract

This study examines the effect of Chinese product import penetration on US manufacturing markups and explores the implications for misallocation. We propose a nonparametric framework that aggregates the identified markup change due to the trade shock into manufacturing TFP based on Baqaee and Farhi (2020). We find that firms in sectors with high import penetration of Chinese products reduce their markups, driven primarily by firms with high initial markups and the change in the markup boosts the allocative efficiency of US manufacturing TFP by about 0.6%.

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1 Introduction

In this paper, we develop a nonparametric framework for aggregating the impact of trade shocks on markups and analyze the impact of Chinese trade on US manufacturing misallocations. Prior studies, particularly Autor et al. (2013, 2014), typically focus on negative trade effects. Conversely, studies such as Jaravel and Sager (2019); Bai and Stumpner (2019); Amiti et al. (2020) focus on beneficial effects, such as lower US consumer prices, through lower markups. We focus on the reduction in misallocation associated with changes in markups.

We propose a simple nonparametric framework based on Baqaee and Farhi (2020) to obtain changes in misallocation from identified changes in markups. Bau and Matray (2020) similarly propose a method to convert changes in identified wedges to TFP, but with different data requirements. Their method requires a quantity of inputs, while our decomposition requires markups and changes in sales share.

We find that firms in sectors with high imports from China suppress their markups, particularly those with higher initial markups, which leads to an increase in allocative efficiency and TFP for US manufacturing of about 0.6%.

2 Conceptual Framework

2.1 Set up

Production Function

We consider an industrial equilibrium following Baqaee and Farhi (2019). The production function is nonparametric, and all firms belong to the manufacturing industry, and we denote this set of firms by $\mathcal{I}$. Each producer $i \in \mathcal{I}$ within a manufacturing industry produces Y_i using external input L_i. The technology of producer i is represented by the CRS production function $F_i(, A_i)$, with productivity A_i as a technology. Without loss of generality, we assume that $\partial logF/\partial logA_i = 1$ in the initial equilibrium. The total output of producer i, Y_i, is either used as an intermediate input by another producer j or used by exogenous final users outside the manufacturing industry. They might be consumers in the US, or they might be exported.

We assume that for all i, producer i minimizes its costs, taking prices as given, and charges a price P_i that is the markup μ_i multiplied by the marginal cost. Labor market clearing condition is;

$$L = \sum_{i \in \mathcal{I}} L_i$$

Expenditure Shares and Domar Weight:

Denote the nominal gross output of the manufacturing sector as $PY = \sum_{i \in \mathcal{I}} P_i C_i$. The share of expenditure in total output is given by

$$b_i = \frac{P_i C_i}{PY}$$

The change in real output is defined as the log change in final output weighted by final expenditure, $dlogY = \sum_{i \in \mathcal{I}} b_i dlogC_i$.

The the sales share of producer i is

$$\lambda_i = \frac{P_i Y_i}{PY}$$

and the factor share of external input is

$$\Lambda = \frac{wL}{PY}$$

The shares are also referred to as Domar weight.

2.2 Allocative Efficiency

The next proposition reformulates the equation in Baqaee and Farhi (2020) using only firm-level variables.

Proposition 1. *The following first-order approximation holds:*

$$dlogTFP = \underbrace{\sum_i \lambda_i dlogA_i}_{\Delta Technical\ Efficiency} + \underbrace{\sum_i \lambda_i \left[\frac{\mu}{\mu_i} - 1\right] dlog\mu_i - \sum_i \lambda_i dlog\lambda_i \frac{\mu}{\mu_i}}_{\Delta Allocative\ Efficiency}$$

$dlog\mu_i$ and $d\lambda_i$ and the initial values of Domar weight and markup are sufficient statistics to calculate the allocative efficiency. μ is given by the harmonic mean of the markup with the firm-level Domar weight as the weight.

$$\mu = \left(\sum_i \lambda_i \frac{1}{\mu_i}\right)^{-1}$$

The first term of allocative efficiency is $\lambda_i \left[\frac{\mu}{\mu_i} - 1\right] dlog\mu_i$ means that a decrease in the markup for a firm i with a higher markup than the average will boost TFP. Intuitively, firms with higher markups are using relatively underproducing, so a lower markup will increase factor input and improve allocative efficiency. The second term implies that if the share of firm i, which has a relatively large markup and is underproducing, increases, allocative efficiency will decrease. We then extend this proposition to aggregate the China shock on allocative efficiency.

Corollary 1. *The impact of China shock (CS) on allocative efficiency of the manufacturing sector is given by*

$$\frac{\Delta logTFP_{AE}}{\Delta CS} = \sum_i \lambda_i^s \left[\frac{\mu}{\mu_i^s} - 1\right] \frac{\partial log\mu_i^s}{\partial CS^s} \Delta CS^s - \mu \sum_i \frac{\lambda_i^s}{\mu_i^s} \frac{\partial log\lambda_i^s}{\partial CS^s} \Delta CS^s$$

where λ_i^s and μ_i^s are the sales share and markup of firm i belonging to sector s. $\mu = \left(\sum_i \lambda_i^s \frac{1}{\mu_i^s}\right)^{-1}$

The proof is obtained by applying the chain rule to proposition 1 and for any variable x we substitute dx with discrete change Δx to obtain the first order approximation. Since China shocks are defined at the subsector level, firms' statistics are also labeled with the subsector s within the manufacturing sector to which they belong. This equation clearly shows what needs to be identified in calculating the impact of trade with China on misallocation. We observe λ_i^s and dCS^s in the data and we could estimate μ_i^s. Therefore, the objects we should identify are $\frac{\partial log\mu_i^s}{\partial CS^s}$ and $\frac{\partial log\lambda_i^s}{\partial CS^s}$.

3 Data and Estimation Strategy

3.1 Data

First, our markup is based on De Loecker et al. (2020). We use sectoral China shocks and its instruments from Autor et al. (2014) and split the data into 1991-1999 and 1999-2007.

Markup

We estimate the markups of US-listed firms in Compustat according to De Loecker et al. (2020)[1],

$$\mu_{it} = \theta^v \frac{Sales_{it}}{COGS_{it}}$$

θ^v is the elasticity of output with respect to variable inputs.

China Shock

We use the China shocks used in Autor et al. (2014).

$$\Delta CS_t^s = \frac{\Delta Import^s}{T_t^s + M_t^s - E_t^s}$$

[1]Our markup is based on Cobb-Douglas assumptions. See De Loecker et al. (2020) for details of the estimation methodology.

where $T_t^s + M_t^s - E_t^s$ is the initial absorption.

To capture the Chinese supply-driven component of US imports from China, we use the following instrumental variables

$$Z_t^s = \frac{\Delta Import_t^{s,OC}}{T_{t-3}^s + M_{t-3}^s - E_{t-3}^s}$$

where $\Delta Import^{s,OC}$is Changes in imports from China from 1991 to 2007 in high-income countries[2] other than the United States, based on industries in which workers were employed in 1988, three years before the base year.

3.2 Estimation Strategy

As Corollary 1 suggests, allocative efficiency can be decomposed as follows.

$$\frac{\Delta logTFP_{AE}}{\Delta CS} = \sum_i \lambda_i^s \left[\frac{\mu}{\mu_i^s} - 1\right] \frac{\partial log\mu_i^s}{\partial CS^s}\Delta CS^s - \mu \sum_i \frac{\lambda_i^s}{\mu_i^s}\frac{\partial log\lambda_i^s}{\partial CS^s}\Delta CS^s$$

For markups, we estimate for two periods, 1991-1999 and 2000-2007 by

$$\Delta \log \mu_{it}^s = \alpha + \beta_1 \Delta CS_t^s + \beta_2 \Delta CS_t^s \times I_{i,init}^{HighMarkup} + \gamma' X + \varepsilon_{it}$$

where $\Delta \log \mu_{it}^s$ is the change in log markup, t is the time (1991-1999 and 2000-2007), ΔCS_{it}^s is the China shock, and $I_{i,init}^{HighMarkup}$ is a dummy variable indicating that markup is higher than the median at initial point (at 1990). The control term X contains a 3-digit Naics dummy, a time dummy, and an initial markup dummy ($I_{i,init}^{HighMarkup}$). The instrumental variables are applied to ΔCS_{it}^s and $\Delta CS_{it}^s \times I_{i,init}^{High\ Markup}$.

We do the same estimation using $\Delta logSale_{it}^s$, the log sales growth rate of the firm.

$$\Delta logSale_{it}^s = \alpha + \beta_1 \Delta CS_t^s + \beta_2 \Delta CS_t^s \times I_{i,init}^{HighMarkup} + \gamma' X + \varepsilon_{it}$$

4 Result

4.1 Empirical Results

Table 1 shows the impact of China shock on the markups: (1) and (2) are specifications that do not use a cross term with the initial markup dummy, and both specifications imply that the markup declines as China's import penetration increases. (3) is our main specification, which adds an interaction term with the dummy for China shocks. According to (3), the markups

[2]These countries are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland.

of high markup firms decline significantly, while the markups of low markup firms become insignificant. In other words, the decline in markups by industry can be interpreted as high markup firms within an industry significantly lowering their markups in response to competition from China. In this regard, Jaravel and Sager (2019) perform quantile regressions of markups using the NTR Gap of Pierce and Schott (2016) and find that the higher the percentile, the larger the drop in markups in response to trade shocks.

Table 2 evaluates China trade's impact on log sales. Models (1) and (2) indicate sales drop with rising Chinese imports. Model (3) adds similar cross terms as in the markup case, showing that firms with lower initial markups tend to see larger sales decreases, albeit insignificantly.

4.2 Aggregation

By using Corollary 1, allocative efficiency can be decomposed as follows.

$$\frac{\Delta logTFP_{AE}}{\Delta CS} = \sum_i \lambda_i^s \left[\frac{\mu}{\mu_i^s} - 1\right] \frac{\partial log\mu_i^s}{\partial CS^s} \Delta CS^s - \mu \sum_i \frac{\lambda_i^s}{\mu_i^s} \frac{\partial log\lambda_i^s}{\partial CS^s} \Delta CS^s$$

For $\frac{\partial log\mu_i^s}{\partial CS^s}$, the results from table 1 (3) can be directly used. As for the change in Domar weight, we have

$$sales_{it}^{CS} = sales_{it} \times (1 + dlog\hat{S}ale_i^s) \Rightarrow$$

$$\hat{\lambda}_{it}^s = \frac{sales_{it}^{CS}}{\sum_i sales_{it}^{CS}}$$

where $sales_{it}^{CS}$ is the counterfactual sales if it were affected only by the China shock.

So we have

$$\frac{\partial log\lambda_i^s}{\partial CS^s} = log\hat{\lambda}_{it}^s - log\lambda_{it}^s$$

The results are as follows,

$$\begin{aligned}\frac{\Delta logTFP_{AE}}{\Delta CS} &= \underbrace{\sum_i \lambda_i^s \left[\frac{\mu}{\mu_i^s} - 1\right] \frac{\partial log\mu_i^s}{\partial CS^s} \Delta CS^s}_{\approx .69(\%)} \underbrace{- \mu \sum_i \frac{\lambda_i^s}{\mu_i^s} \frac{\partial log\lambda_i^s}{\partial CS^s} \Delta CS^s}_{-.11(\%)} \\ &\approx 0.58(\%)\end{aligned}$$

Therefore, we conclude that the considerable reduction in markups by high markup firms in response to China's increased import penetration will have improved US manufacturing misallocation and boosted US manufacturing productivity by 0.6 percent.

5 Conclusion

In this paper, we used firm-level data to estimate the causal effect of the penetration of Chinese imports on US manufacturing markups and its magnitude on the overall misallocation of US manufacturing. We conclude that firms in sectors with high import penetration of Chinese products will reduce their markups and that markup reduction will be driven primarily by firms with high initial markups. This markup change improves the allocative efficiency of US manufacturing, boosting TFP by about 0.6%.

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Tables

Table 1: Change in markup: 1991-2007:1992-2007

	(1) TSLS_1	(2) TSLS_2	(3) TSLS_3	(4) TSLS_4	(5) TSLS_5	(6) OLS1
China Shock	-0.571**	-0.596***	-0.204	-0.204	-0.340**	-0.297**
	(0.234)	(0.188)	(0.203)	(0.155)	(0.152)	(0.149)
CS× Dummy			-0.898***	-0.898***	-0.614***	
			(0.325)	(0.202)	(0.222)	
Year	Yes	Yes	Yes	Yes	Yes	Yes
Ind	Yes	Yes	Yes	Yes	Yes	Yes
Init_markup_dum	No	Yes	No	No	Yes	No
N	1846	1846	1846	1846	1846	1846
vce	robust	cluster	robust	cluster	cluster	robust

Standard errors in parentheses. Clustering is at the 3-digit Naics level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Change in log sales: 1991-2007

	(1) TSLS_1	(2) TSLS_2	(3) TSLS_3	(4) TSLS_4	(5) OLS1
China Shock	-0.865***	-0.865***	-0.947***	-0.947***	-0.373*
	(0.280)	(0.174)	(0.349)	(0.331)	(0.219)
CS× Dummy			0.200	0.200	
			(0.393)	(0.512)	
Year	Yes	Yes	Yes	Yes	Yes
Ind	Yes	Yes	Yes	Yes	Yes
N	1846	1846	1846	1846	1846
vce	robust	cluster	robust	cluster	robust

Standard errors in parentheses. Clustering is at the 3-digit Naics level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix1: Proof for Propositon1

Start from the general formula from Baqaee and Farhi (2020).

$$dlogTFP = \sum_i \lambda_i dlogA_i - \sum_i \tilde{\lambda}_i d\log\mu_i - \sum_f \tilde{\Lambda}_f d\log\Lambda_f$$

Since we are assuming a one-factor horizontal economy, $\tilde{\lambda}_i = \lambda_i$ and $\tilde{\Lambda}_f = 1$ and $dlogA = 0$. Then,

$$\begin{aligned}
dlogTFP_{AE} &= -\sum_i \lambda_i d\log\mu_i - d\log\Lambda \\
&= -\sum_i \lambda_i d\log\mu_i + d\log\mu \\
&= -\sum_i \lambda_i d\log\mu_i - \mu\sum d\lambda_i\frac{1}{\mu_i} + \mu\sum\lambda_i\frac{1}{\mu_i}dlog\mu_i \\
&= \sum\lambda_i\left[\frac{\mu}{\mu_i} - 1\right]dlog\mu_i - \mu\sum dlog\lambda_i\frac{\lambda_i}{\mu_i}
\end{aligned}$$

Here, the aggregate markup μ is given by the harmonic mean of the markup with the firm-level Domar weight as the weight.

$$\mu = \left(\sum_i \lambda_i\frac{1}{\mu_i}\right)^{-1}$$

Appendix2: Aggregation formula for the general case

This paper has derived an aggregate equation for China's impact on misallocation, assuming a horizontal economy for simplicity. However, from another data source (USKLEM), we can calculate the sum of Domar weight of the manufacturing sector in the following way

$$\sum \lambda_f = \sum_f \frac{Sales_f}{\sum_{f'} ValueAdded_{f'}} \approx 2.7$$

The sum of the dormer weights is far from 1, and the assumption of a horizontal economy may underestimate the change in allocative efficiency. Therefore, we derive a formula based on the general IO structure assumption. However, it is not easy to obtain IO structure data at the US firm-level, and additional assumptions on the industry structure are required for real-world application. Therefore, we focus on the horizontal economy in this paper.

To do so we define the IO matrices. First, the revenue-based IO matrix is denoted by

$$\Omega_{ij} = \frac{P_j Y_{ij}}{P_i Y_i}$$

which is the expenditure on j as a share of the income of i, where j is an intermediate goods input within the manufacturing sector or an external input of factor f.

Similarly, the cost-based IO matrix, $\tilde{\Omega}$ is defined by

$$\Omega_{ij} = \frac{P_j Y_{ij}}{\underbrace{\sum_j P_j Y_{ij}}_{total\ cost}} = \frac{\Omega_{ij}}{\mu_i}$$

which means that j is a share of the total cost of i.

The revenue-based (Ψ) and cost-based ($\tilde{\Psi}$) Leontief inverse can be written as

$$\Psi = (I - \Omega)^{-1} = I + \Omega + \Omega^2 + \dots$$

$$\tilde{\Psi} = \left(I - \tilde{\Omega}\right)^{-1} = I + \tilde{\Omega} + \tilde{\Omega}^2 + \dots$$

Whereas Ω and $\tilde{\Omega}$ record direct exposures from one producer to another in terms of revenues and costs, respectively, Ψ and $\tilde{\Psi}$ instead record direct and indirect exposures through the IO network.

The accounting identity

$$P_i Y_i = P_i C_i + \sum_j P_i Y_{ji} = b_i \left(\sum_i P_i C_i \right) + \sum_j \Omega_{ij} P_j Y_j$$

relates Domar weights to the Leontief inverse via

$$\lambda' = b'\Psi = b'I + b'\Omega + b'\Omega^2 + \dots$$

Similarly, we define the cost-based Domar weights as follows

$$\tilde{\lambda}' = b'\tilde{\Psi} = b'I + b'\tilde{\Omega} + b'\tilde{\Omega}^2 + \dots$$

Proposition 2. *In a one-factor economy with IO structure, the change in the efficiency of TFP allocation with the change in markup is given by*

$$dlogTFP_{AE} = \sum \lambda_i \left[\frac{\mu}{\mu_i} - \frac{\tilde{\lambda}_i}{\lambda_i}\right] dlog\mu_i + \sum_i \lambda_i \frac{\left(1 - \frac{1}{\mu_i}\right)}{\Lambda_L} dlog\lambda_i$$

where Λ_L *is aggregate factor share and* $\Lambda_L = 1 - \sum_i \lambda_i \left(1 - \frac{1}{\mu_i}\right)$*. Therefore,* $dlog\mu_i$ *and* $d\lambda_i$ *and the initial values of cost-based and revenue-vased Domar weight and markup are sufficient statistics to characterize the allocative efficiency.*

Proof. Again starts from Baqaee and Farhi (2020),

$$\begin{aligned} dlogTFP_{AE} &= \sum_f \tilde{\Lambda}_f dlogL_f + \sum_i \tilde{\lambda}_i dlogA_i - \sum_i \tilde{\lambda}_i d\log\mu_i - \sum_f \tilde{\Lambda}_f d\log\Lambda_f \Leftrightarrow \\ &= -\sum_i \tilde{\lambda}_i d\log\mu_i - d\log\Lambda_L \end{aligned}$$

Note that

$$\begin{aligned} \Lambda_L &= 1 - \sum_i \lambda_i \underbrace{\left(1 - \frac{1}{\mu_i}\right)}_{profitshare} \Leftrightarrow \\ &= \left(1 - \sum_i \lambda_i\right) + \sum_i \lambda_i \frac{1}{\mu_i} \end{aligned}$$

Take a total derivative,

$$
\begin{aligned}
d\Lambda_L &= -d\left\{\sum_i \lambda_i\left(1-\frac{1}{\mu_i}\right)\right\} \Leftrightarrow \\
dlog\Lambda_L\frac{d\Lambda_L}{dlog\Lambda_L} &= -\sum_i d\lambda_i\left(1-\frac{1}{\mu_i}\right)+\sum_i \lambda_i d\left(\frac{1}{\mu_i}\right) \Leftrightarrow \\
dlog\Lambda_L\Lambda_L &= -\sum_i d\lambda_i\left(1-\frac{1}{\mu_i}\right)-\sum_i \lambda_i\frac{1}{\mu_i}dlog\mu_i \Leftrightarrow \\
dlog\Lambda_L &= -\frac{1}{\Lambda_L}\sum_i d\lambda_i\left(1-\frac{1}{\mu_i}\right)-\sum_i \lambda_i\frac{1}{\mu_i}\frac{1}{\Lambda_L}dlog\mu_i \Leftrightarrow \\
&= -\mu\sum_i d\lambda_i\left(1-\frac{1}{\mu_i}\right)-\sum_i \lambda_i\frac{\mu}{\mu_i}dlog\mu_i
\end{aligned}
$$

Therefore,

$$
\begin{aligned}
dlogTFP_{AE} &= -\sum_i \tilde{\lambda}_i d\log\mu_i - d\log\Lambda_L \Leftrightarrow \\
&= -\sum_i \tilde{\lambda}_i d\log\mu_i + \sum_i d\lambda_i\frac{1}{\Lambda_L}\left(1-\frac{1}{\mu_i}\right)+\sum_i \lambda_i\frac{1}{\mu_i}\frac{1}{\Lambda_L}dlog\mu_i \Leftrightarrow \\
&= -\sum_i \tilde{\lambda}_i d\log\mu_i + \sum_i d\lambda_i\frac{1}{\Lambda_L}\left(1-\frac{1}{\mu_i}\right)+\sum_i \lambda_i\frac{\mu}{\mu_i}dlog\mu_i \Leftrightarrow \\
&= \sum \lambda_i\left[\frac{\mu}{\mu_i}-\frac{\tilde{\lambda}_i}{\lambda_i}\right]dlog\mu_i+\sum_i \lambda_i\frac{\left(1-\frac{1}{\mu_i}\right)}{\Lambda_L}dlog\lambda_i
\end{aligned}
$$

where

$$
\Lambda_L = \left[\left(1-\sum_i \lambda_i\right)+\sum_i \lambda_i\frac{1}{\mu_i}\right]
$$

$\square$