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 U.S. manufacturing markups using firm-level data and explores the implications for misallocation in the U.S. manufacturing sector. To derive aggregate implications, we propose a nonparametric framework that aggregates the identified estimates 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 U.S. manufacturing TFP by about 0.6%.

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1 Introduction

Can international trade reduce misallocation? Misallocation distorts the efficient allocation of factors by wedges, including markups, and reduces aggregate TFP. This paper explores the impact of trade with China on the misallocation of U.S. manufacturing firms through changes in the distribution of markups. While recent evidence from microdata shows that increased trade with China has had a significant negative impact on the U.S. labor market (Autor et al. (2014); Pierce and Schott (2016)), the impact on U.S. misallocation has not been studied. Particularly relevant studies are Jaravel and Sager (2019); Bai and Stumpner (2019); Amiti et al. (2020), which studied the impact of trade with China on the U.S. CPI. They argued that trade with China reduced the markup in the U.S., which pushed down the U.S. CPI. While this study is suggestive, it does not allow us to know the impact on misallocation. What is important in measuring the impact on misallocation is not the change in the level of markups but the change in the dispersion of markups.

Therefore, this paper will use firm-level markups to identify the effect of trade with China on markups and aggregate this effect on TFP in the U.S. manufacturing sector. Specifically, we explore how the markups estimated using De Loecker et al. (2020b)'s method respond to increases in trade with China. However, as is well-known, estimating causality from increased imports from China is difficult due to omitted variable bias and the possibility of reverse causality. For this reason, we use the instrumental variables of Autor et al. (2014) in our estimation. As for aggregating the effects estimated at the micro-level to the manufacturing sector as a whole, we use a sufficient statistics approach using the equation proposed in Baqaee and Farhi (2020). This framework provides sufficient statistics to calculate the impact of misallocation on aggregate productivity and tells us what data we need and what objects we need to identify at the micro-level.

Our main conclusions are as follows: First, we find that firms in sectors with a high share of Chinese product imports reduce their markups and that markup reductions are driven primarily by firms with high initial markups. Looking at this markup change through the lens of our sufficient statistic approach, we find that this reduction in markup dispersion increases the allocative efficiency of U.S. manufacturing, equivalent to a boost in TFP of about 0.6 percent.

Related literature and our contribution

This study contributes to three strands of literature. The first is the impact of trade with China on the United States, in which much of the literature emphasizes the negative aspects of trade with China. The most well-known is the negative impact on employment, for which there is extensive literature (Autor et al. (2013, 2014), etc.). On the other hand, there has been a growing literature on the positive aspects of trade with China (Galle et al. (2017); Wang et al. (2018); Caliendo et al. (2019)). The literature of particular relevance to our study includes Jaravel and Sager (2019); Bai and Stumpner (2019); Amiti et al. (2020), who find that increased trade with China has benefited U.S. consumers through lower U.S. consumer prices; and Jaravel and Sager (2019) argue that lower markups for U.S. firms due to increased competition led to lower prices. While their work is suggestive, it is not easy to understand the impact of misallocation from their study. What matters for whether misallocation is eliminated or increased is the dispersion of the markup. Our results focus on this point, highlighting a new aspect of trade with China and complementing existing studies.

The second is the pro-competitive effects of trade. For example, Edmond et al. (2015) argue that Taiwan's accession to the WTO has increased allocative efficiency by reducing misallocation. On the other hand, Arkolakis et al. (2018) conclude that the pro-competitive effects of trade are negative. The change in the distribution of markups in these papers relies on specific model assumptions, and Arkolakis et al. (2018) emphasize that the pro-competitive effect can be positive or negative by changing the model assumptions. Therefore, it is important to identify and obtain implications of changes in the distribution of empirical markups with respect to a particular episode of trade liberalization. In this regard, we derive macro-level effects by aggregating the causal effects estimated in firm-level micro data without committing to a specific endogenous mechanism of markups. Our analysis also contributes to the literature by shedding new light on the impact of trade with China on the allocative efficiency of U.S. manufacturing.

Finally, this study contributes to the macroeconomics literature that quantifies the importance of misallocation to collective outcomes (Restuccia and Rogerson (2008); Hsieh and Klenow (2009); Bartelsman et al. (2013); Baqaee and Farhi (2020)). Most of these studies focus on the relationship between misallocation, as measured by the dispersion of revenue total factor productivity (TFPR), but they do not reveal the specific sources of misallocation. Another problem is that the measurement error can inflate estimates of misallocation, and this problem is particularly problematic when comparing the magnitude of misallocation among countries with different magnitudes of measurement error. In this regard, our study reveals a specific origin of misallocation: the impact of China shocks on U.S. manufacturing misallocation. Also, the measurement error problem may be small because the measurement error at different points in time within the U.S. will be smaller than the difference in measurement error across nations. Related to this point, Bau and Matray (2020) also quantify the effect of financial liberalization in India by identifying changes in misallocation using the method of natural experiments, but they do not identify which wedge changes caused the changes in misallocation.

The remainder of this paper is as follows. First, in Section 2, we derive a theory that links the distribution of firm-level markups to the macro-level reallocation effect and clarify what needs to be identified using microdata. Section 3 describes the data and estimation strategy used for estimation. Section 4 discusses the results of the empirical analysis and the results of aggregate using it.

2 Conceptual Framework

This section derives a theoretical equation to aggregate China's causal effects on markups at the firm-level to the macro-level. To this end, we first introduce the model setup and the definition of each variable. The description here is essentially based on Baqaee and Farhi (2019, 2018), which extends the Baqaee and Farhi (2020) formula to apply to a subset of general equilibrium systems particularly convenient for our study, which focuses on the U.S. manufacturing sector.

2.1 Set up

Aggregate Productivity in Manufacturing

In an efficient economy, output changes as inputs change or as production technology changes. Thus, by subtracting the growth of inputs from the growth of outputs, we can construct the so-called Solow residuals. However, this intuition breaks down in an inefficient economy. This is because the allocative efficiency of factors of production can be changed by micro-level shocks. In this section, we show how to decompose the TFP growth rate of manufacturing into changes in pure technology and changes in allocative efficiency.

Model Environment

In this section, we consider an industrial equilibrium model of the U.S. manufacturing sector. Here we consider a more general economy with an IO structure in the manufacturing sector, and in later applications, we consider a special case of this economy, the horizontal economy. The production function is nonparametric, and all firms belong to one group, 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 inputs L_{if} and $f \in \mathcal{F}$ with intermediate inputs Y_{ij} of j produced within the manufacturing industry.

The technology of producer i is represented by the CRS production function $F_i(, A_i)$, with productivity A_i as a production technology. Without loss of generality, we assume that $\partial log F / \partial log A_i = 1$ 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 final users outside the manufacturing industry. They might be consumers in the U.S., or they might be exported abroad.

Since we are considering a partial equilibrium model, these external demands are exogenous. The total amount of external inputs used by all firms in is L_f for each f.

We make two basic assumptions here. The first assumption is 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. The second assumption is market clearing,

$$Y_i = C_i + \sum_{i \in \mathcal{I}} Y_{ji} \qquad for\, all\, i$$
$$L_f = \sum_{i \in \mathcal{I}} L_{if} \qquad for\, each\, f \in \mathcal{F}$$

Expenditure Shares:

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, $dlogY = \sum_{i \in \mathcal{I}} b_i dlogC_i$.

Domar Weights and Input-Output (IO) Matrices:

The the sales share of producer i is

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

and the factor share of external input f is

$$\Lambda_f = \frac{P_f L_f}{PY}$$

The shares is also referred to as the (revenue-based) Domar weight.

Next, 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

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

Finally, for a factor f we denote Λ_f and $\tilde{\Lambda}_f$ instead of λ_f and $\tilde{\lambda}_f$

Shocks:

The shocks in this model are productivity $dlogA$, external input $dlogL$, and markup wedge $dlog\mu$. These changes can be caused by some deeply endogenous mechanism or they can be exogenous. In this paper, without assuming any specific endogenous mechanism, we identify the change in the markup wedge $dlog\mu$ caused by the China shock from microdata and perturb the model with it.

2.2 Allocative Efficiency

Based on the above setup, we derive an equation that aggregates the micro-level causal effects on the markup of the China shock into macro-level effects. In the subsequent analysis, we assume a one-factor horizontal economy. A horizontal economy is a special case of the economy described in section 2.1, in which there is no IO linkage within the manufacturing sector. Each firm uses a single input, and all products are treated as final production. The horizontal economy assumption makes it easier to relate the data to the model and provides an intuitive insight into the relationship between individual firm markups and allocative efficiency. In Appendix2, we also discuss the aggregation formula when this assumption is relaxed.

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

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

Therefore, $dlog\mu_i$ 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 left-hand side is the change in aggregate output minus the change in the contribution of production factors, which corresponds to Solow residual. The right-hand side decomposes the change in the Sorrow residual into the contribution of the technological productivity of individual firms and the reallocation effect. In other words, the proposition shows that the change in markup, Domar weight, and initial values in the horizontal economy are sufficient statistics to calculate the variation in allocative efficiency. It is important to note here that changes in factors and output constitute aggregate TFP and are not necessary to obtain allocative efficiency. Similarly, if we are interested only in allocative efficiency, individual firms' productivity changes, $dlogA$ are also unnecessary.

There is a clear interpretation of this equation. The first term of allocative efficiency is $\lambda_i \left[\frac{\mu}{\mu_i} - 1\right] dlog\mu_i$, which means that a decrease in the markup for a firm i with a higher (lower) markup than the average will push up (lower) TFP. In other words, changes that reduce the dispersion of markups will improve allocative efficiency. Intuitively, firms with markups higher (lower) than the average markup are using relatively under (over) factor, so a lower markup will increase (decrease) factor input and improve allocative efficiency. In addition, the relative contribution is more prominent the higher Domar weight. The second term implies that when firm i's share increases, allocative efficiency declines if the firm's markup is relatively small. This is because firms with smaller markups are overproducing, so an increase in their share implies a social loss. We then extend this proposition to derive a formula for our purpose: to aggregate the impact of trade with China on allocative efficiency.

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

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

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. This equation clarifies that the fluctuations in markups and Dormer weights obtained in Proposition 1 are due to the China shock. The rest of the intuition is the same as in Proposition 1. 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 is practical and clearly shows what needs to be identified in calculating the impact of trade with China on misallocation. First, we observe λ_i^s and dCS^s in the data and we could estimate μ_i^s. The average markup, μ, can also be calculated using the harmonic mean formula. Therefore, the objects we should identify are $\frac{\partial log\mu_i^s}{\partial CS^s}$ and $\frac{\partial log\lambda_i^s}{\partial CS^s}$. In the next section, we will explain the estimation strategy to identify these two objects.

3 Data and Estimation Strategy

In the section, we build on the previous discussion to discuss estimation strategies for identifying the objects of interest.

3.1 Data

Our primary analysis relies on two data sources; U.S. firm-level data from Compustat and China shocks and their appropriate instrumental variables from Autor et al. (2014)[1]. First of all, our primary outcome variable, the markup, is based on De Loecker et al. (2020b). For China shocks, we use sectoral China shocks from Autor et al. (2014), who uses their definition of "sic87dd" to define sectors, so we use the crosswalk file published by David Dorn to convert the Compustat's sic sectors and then connect the data. Sectors for which no corresponding China shocks were dropped from the sample. Besides, in calculating changes in markups and Domar weights, we followed Autor et al. (2014) and split the data into 1991-1999 and 1999-2007, focusing on firms that survived in both periods and calculating changes in each variable. As

[1] We use the China Shock and instrumental variables in Autor et al. (2014) prepared by David Dorn.

for Domar weight calculation, after narrowing down the sample using the method described above, we calculated each year's Domar weights from sales by dividing the firm's sales by the total sales for each year. Therefore, the sum of Domar weights is one for each year, consistent with our horizontal economy assumption.

Markup

Following the method of De Loecker et al. (2020b)[2] (production function approach), we estimate the markups of U.S. listed companies registered in Compustat.

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

θ^{ν} is the elasticity of output with respect to variable inputs.

China Shock

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

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

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

A concern with using CS_i^s as a measure of trade exposure is that the observed changes in import penetration may partially reflect domestic shocks to the U.S. industry. To capture the Chinese supply-driven component of U.S. imports from China, we use the following instrumental variables as follows.

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

where $\Delta Import^{s,OC}$is Changes in imports from China from 1991 to 2007 in high-income countries[3] other than the United States, based on industries in which workers were employed in 1988, three years before the base year. The motivation for the instrumental variable is that high-income economies are as exposed as the U.S. to growth in Chinese imports caused by supply shocks originating in China. Autor et al. (2014) discessed that this variable has sufficient explanatory power for U.S. import penetration in China and is appropriate as an instrumental variable.

[2]The markup we use is the variable "mu_9" from their replication file (De Loecker et al. (2020a). This is an estimate of the production function based on Cobb-Douglas assumptions. See De Loecker et al. (2020b) for details of the estimation methodology.

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

3.2 Estimation Strategy

We have shown in Section 2, Corollary 1, that allocative efficiency can be decomposed as follows.

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

This subsection will discuss strategies for identifying $\frac{\partial log\mu_i^s}{\partial CS^s}$ and $\frac{\partial log\lambda_i^s}{\partial CS^s}$. As is well-known, estimating causality from increased imports from China is difficult due to omitted variable bias and the possibility of reverse causality. For this reason, we use the instrumental variables of Autor et al. (2014) in our estimation. Also, since China shock is a variable defined at the sector level, it cannot capture changes in sector misallocation. In this regard, similar to this paper, Bau and Matray (2020), who analyze the effects of financial liberalization in India using the framework of Baqaee and Farhi (2020), consider cross terms between liberalized sectors and firms that were highly distorted before regulatory changes.

The specific estimation formulas are as follows. For markups, we estimate for two periods, 1991-1999 and 2000-2007. The estimated equations are as follows.

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

where $\Delta \log \mu_{it}^s$ is the change in log markup, t is the time (1991-1999 and 2000-2007), CS_{it}^s is the China shock (change in import penetration by sector), 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 markup is a change from the previous period, and fixed effects are removed, but we are also considering a specification that explicitly adds an initial markup dummy for robustness checks. The instrumental variables are applied to CS_{it}^s and $CS_{it}^s \times I_{i,init}^{High\,Markup}$.

In the case of Domar weights, we do the same estimation using $\Delta logSale_{it}^s$, the log sales growth rate of the firm.

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

The definition of variables and the application of an instrumental variable is the same as for markup.

4 Result

4.1 Empirical Results

This section will estimate the two equations $dlog\mu_{i,t}$ and $dlogSale_i^s$ introduced in the previous section, and then aggregate them using the equation of Corollary 1 in Section 2. Table 1 shows the impact of China shock on the markups:

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

(1) and (2) are specifications that do not use an intersection 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 intersection term with the dummy for China shocks. According to (3), the markups 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, which is consistent with our results. In (4), we use cluster robust standard errors, and in (5), we explicitly add initial markup dummies, but the significance of the cross terms continues to hold in both specifications. The results in (6) are from OLS, and the coefficients are smaller than in (1), indicating the importance of controlling for endogeneity by IV.

Table 2 measures the impact of China shock on the log sales:

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

Specifications (1) and (2) do not use the intersection term with the initial markup dummy, and both specifications imply that sales decline as the prevalence of Chinese imports increases. In (3), we add the same cross terms as in the markup case. According to (3), although not significant, the coefficient of the cross term is positive, and firms that initially had a lower markup tend to have a larger decrease in sales. (5) is the result of OLS and shows a significant decrease in the coefficient compared to (1), indicating the importance of controlling for endogeneity by IV.

4.2 Aggregation

In this subsection, we use the results obtained in 4.1 to calculate the impact of the China shock on the U.S. manufacturing sector's allocative efficiency. We have shown in Section 2, Corollary

1, that allocative efficiency can be decomposed as follows.

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

For $\frac{\partial log\mu_i^s}{\partial CS^s}$, the results from table 1 can be directly used. We will use the value in spec (3), which takes into account the heterogeneity in the sector.

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

$$dlo\hat{g}\lambda_{it}^s = log\hat{\lambda}_{it}^s - log\lambda_{it}^s$$

The results are as follows,

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

Therefore, we conclude that the considerable reduction in markups by high markup firms in response to China's increased import penetration may have improved U.S. manufacturing misallocation and boosted U.S. manufacturing productivity by 0.6 percent. This corresponds to about $6,257.92 million[4], suggesting that it could partially compensate those negatively affected in the labor market by the trade shock.

5 Conclusion

In this paper, we used firm-level data to estimate the causal effect of the penetration of Chinese imports on U.S. manufacturing markups and its magnitude on the overall misallocation of U.S.

[4] 0.6% of manufacturing value-added in U.S. KLEM of 1991

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 U.S. manufacturing, boosting TFP by about 0.6%.

Finally, we discuss the remaining issues. First, in this paper, we derived an aggregate equation for the impact of the China shock on misallocation by assuming a horizontal economy for simplicity. However, as discussed in the appendix, the sum of Domar weight of the U.S. manufacturing sector is about 3, far from 1. Since network structure usually tends to amplify shocks, the assumption of horizontal economies may underestimate changes in allocative efficiency. However, it is not easy to obtain detailed data on firm-level IO structure in the U.S. A realistic approach would be to use, for example, information from IO tables or sectoral markups under certain simplifying assumptions. These are issues that need to be addressed in the future.

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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 U.S. 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.

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

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

$\square$