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International Influences on Japanese Supply Chains

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Abstract

This paper investigates the transmission mechanism of Chinese productivity shocks through industry-level and firm-level networks in the Japanese manufacturing sector using an instrumental variable approach. We find that increased Chinese productivity in a particular industry negatively affects Japanese suppliers of Japanese firms in that industry (upstream propagation) and positively affects their Japanese corporate customers (downstream propagation). This contrasts the recently studied case of the United States, which did not lead to evidence for downstream propagation of such shocks.

Keywords: Macroeconomic shock propagation, Firm networks, International trade

JEL classification codes: E32, F41.

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1 Introduction

This paper investigates how variation in imports from China is transmitted through industry- and firm-level networks in Japan.[1] To identify an exogenous component of the variation in imports from China, we employ instrumental variable estimators similar to those in Autor, Dorn and Hanson (2013a): We use the import values of eight other developed countries from China to instrument for Japanese imports from China. The import values of other countries should not be related to unobserved changes in productivity in the Japanese economy. Acemoglu, Akcigit and Kerr (2015b) use the U.S. industry-level network data to study how the rising imports from China affect the U.S. economy and how the shocks are transmitted through industry input-output networks. They found that exogenous increases in the imports from China have a particular transmission pattern: When the imports from China increase in customer industries, the original industries[2] are negatively affected (upstream effects) but increased imports from China in supplier industries do not have any effect on the original industry. It means that import competition with China negatively affects the U.S. manufacturing industries, especially those whose customers produce the commodities that are competitive with goods imported from China.

We first analyze industry-level network effects by using the input-output table data. In agreement with Acemoglu, Akcigit and Kerr (2015b), we find that when customer industries of a given industry experience a rise in imports from China, then the original industry experiences a drop in value-added growth. This negative upstream effect can be interpreted as follows: increased presence of Chinese goods in customer industry reduces demand for the products of Japanese firms in that industry,

[1] We use data from mainland China, which excludes Hong Kong and Taiwan.

[2] We refer to an industry of interest as the "original industry". This industry buys intermediate inputs from "supplier industries" and sells its output to "customer industries".

which in turn reduce their inputs purchased from the original industry.

Interestingly, we find a result different from that of Acemoglu, Akcigit and Kerr (2015b) for the case when the imports from China exogenously increase in the supplier industries: in our case the original industry would experience an increase in value-added growth, whereas in their analysis this effect was found insignificant.

Next, we analyze firm-level network effects using supplier-customer links. By using firm relationship data and industry-level import data, we investigate how companies are affected when the industry to which its suppliers or customers belong experiences an exogenous rise in imports from China. Similarly to our industry-level analysis, we find strong positive downstream effects: Firms sales increase when the industry to which its suppliers belong experiences the increased imports from China. In this firm-level analysis we also find negative upstream effects. Their magnitude is smaller than that of the downstream effects.

Overall, our results highlight the strong transmission pattern of the exogenous variation of Japanese imports from China: The rise in the imports from China in upstream (input-supplying) industry positively affects downstream firms and industries. While many papers report that the dramatic rise in the imports from China has negatively affected manufacturing industries in developed countries, this paper suggests that a substantial number of Japanese manufacturing companies may have benefitted from it.

This paper contributes to several strands of literature. It relates to the network literature that examines how small shocks are transmitted and propagated through economies to cause macroeconomic fluctuations. One possible explanation for the transmission mechanism through firm-networks is a shock propagation mechanism through production networks. This idea has been valued less because idiosyncratic shocks are to be washed out when we aggregate them across firms or industries due to a law of large numbers. However, Gabaix (2011) shows that this argument breaks down if the distribution of firm sizes is fat-tailed, and the idiosyncratic movements of large firms can explain a major part of macroeconomic fluctuations. Earlier works on network based shock propagation mechanism theoretically show the importance of industry-level input-output networks for the aggregation of industry-specific shocks (Long Jr and Plosser (1983); Bak, Chen, Scheinkman and Woodford (1993); Horvath (1998, 2000); Acemoglu, Carvalho, Ozdaglar and Tahbaz-Salehi (2012)).[3] The empirical evidence is consistent with the theoretical literature (Carvalho (2008); Di Giovanni and Levchenko (2010)). While there has been considerable research on industry-level input-output networks and their formation, little work has considered the supplier-customer relationships between firms until recently. Some of the recent papers focusing on firm-level network data study the production network effects of natural disasters, such as the Great Eastern Japan Earthquake in 2011 (Carvalho, Nirei, Saito and Tahbaz-Salehi (2014); Boehm and Flaaen (2014); Barrot and Sauvagnat (2014); Todo, Nakajima and Matouš (2015a)). Other papers examine the effect of the geographic structure of supply chain networks on firms' productivities and innovation capability (Bernard, Moxnes and Saito (2014, 2015); Todo, Matouš and Inoue (2015b); Furusawa, Inui, Ito and Tang (2015)). We contribute to these strands of literature by documenting that the propagation of international trade shocks through input-output and supplier-customer networks can be a powerful driver of macroeconomic fluctuations.

This paper also contributes to the literature that examines the impact of the imports from China in developed countries. Several studies conclude that the increase in U.S. imports from China has adverse effects on U.S. labor market (Autor, Dorn

[3]For empirical evidence on the production network structure itself, see Atalay, Hortaçsu, Roberts and Syverson (2011), and references therein.

and Hanson (2013a); Autor, Dorn, Hanson, Song et al. (2013b)). On the other hand, the impact of imports from China in Japan seems to be different from the case of the U.S. Taniguchi (2014) obtains evidence that the growth in imports from China positively affected manufacturing employment growth at the prefecture level in Japan. This result contrasts the findings of Autor, Dorn and Hanson (2013a) for local labor markets in the U.S. She concludes that the positive effects of import growth from China in Japanese labor market are mainly caused by an increase in intermediate imports. Our findings give other evidence that the increase in imports from China have positive effects on Japanese manufacturing firms and suggest that the effects are propagated through industry- and firm-level networks.

The remainder of the paper is organized as follows. In Section 2, we present our empirical strategy and data and show industry-level results. Section 3 presents the firm-level analysis, and Section 4 concludes. Supporting material is in the online appendix.[4]

2 Industry-level analysis of productivity shock propagation

2.1 Empirical strategy for the firm-level instrumental variable estimation

Our industry-level empirical strategy is analogous to that of Acemoğlu, Akcigit, and Kerr (2015). The relationship we would like to estimate using instrumental variables

[4]https://sites.google.com/site/fabinger/filecabinet/InfluencesOnSupplyChainsOnlineAppendix.pdf

is[5]

$$\Delta \ln y_{i,t} = \eta_t + \psi \Delta \ln y_{i,t-1} + \beta^{own} \triangle\phi_{i,t-1} + \beta^{up} \triangle\phi_{i,t-1}^{upstream} + \beta^{down} \triangle\phi_{i,t-1}^{downstream} + \epsilon_{i,t}. \tag{1}$$

Here i is an industry index, η_t denotes a full set of time fixed effects, $\epsilon_{i,t}$ is an error term, and $y_{i,t}$ stands for real value added from the RIETI JIP Database 2014, Growth Accounting.[6] The key regressors are $\triangle\phi_{i,t-1}$, $\triangle\phi_{i,t-1}^{upstream}$, and $\triangle\phi_{i,t-1}^{downstream}$, and they are designed to capture changes Chinese trade influence on industry i, its customer industries, and its supplier industries, respectively. They are constructed as follows.

Industry i's the industry's own direct trade influence $\phi_{i,t}$ is defined to be the negative of the ratio of $I_{China\to Japan,i,t}$, the value of Japanese imports from China in industry i in year t, and $S_{Japan,i,1995}$, the Japanese market size of industry i in year 1995, which is the initial year of our data:

$$\phi_{i,t} = -\frac{I_{China\to Japan,i,t}}{S_{Japan,i,1995}}. \tag{2}$$

In general, we use Δ to denote a one-year time difference, so the own trade shock of industry i is $\triangle\phi_{i,t} \equiv \phi_{i,t} - \phi_{i,t-1}$.

The customer and supplier industry network influences are constructed as in Acemoğlu, Akcigit, and Kerr (2015). The variable $\phi_{i,t}^{upstream}$ represents Chinese trade influences transmitted to industry i from its customer industries:

$$\phi_{i,t}^{upstream} = \sum_j M_{i\to j}^{output,1995} \phi_{j,t}. \tag{3}$$

[5]For a theoretical motivation of this specification, see Acemoğlu, Akcigit, and Kerr (2015). Note that $\Delta \ln y_{i,t-1}$ is included in the estimated equation merely as a control and is not intended to mean that, say, lagged value-added growth is the causal reason for current value-added growth.

[6]In the model of Acemoğlu, Akcigit, and Kerr (2015), y_t represents output and they use value added as a proxy of output in their empirical analysis. For comparison, we also use value added.

The matrix $M_{i \to j}^{output,1995}$ is the output Leontief inverse matrix[7] based on the Japanese input-output table from the RIETI for the year 1995. It is predetermined and does not depend on the time index t. Similarly, $\phi_{i,t}^{downstream}$ represents Chinese trade influences transmitted to industry i from its supplier industries:

$$\phi_{i,t}^{downstream} = \sum_{j} M_{j \to i}^{input,1996} \phi_{j,t}, \tag{4}$$

where the matrix $M_{j \to i}^{intput,1996}$ is the input Leontief inverse matrix based on the same input-output table.

To avoid possible confusion, we should clarify the meaning of the terms "downstream" and "upstream", since they may seem counterintuitive. We speak of "upstream effects" when shocks to customers of an industry flow up the input-output chain and have an impact on that industry. We speak of "downstream effects" when shocks to suppliers of an industry flow down the input-output chain and have an impact on that industry. Therefore, "upstream effects" stem from shocks to customers of an industry, and "downstream effects" stem from shocks to suppliers of an industry. In other words, "upstream" and "downstream" are used in the directional sense, not in the position sense.

The shock variables are clearly suffering from endogeneity problem because imports from China will increase when the industry in question has lower productivity growth for other reasons. To deal with this problem we perform and instrumental variable estimation, and motivated by Autor, Dorn and Hanson (2013a) and Acemoğlu, Akcigit, and Kerr (2015), we choose instrumental variables based on the change in import penetration from China to eight non-Japan developed countries, Australia, Denmark, Finland, Germany, New Zealand, U.S., Spain, and Switzerland:

[7] The construction of these matrices is further clarified in the online appendix.

$$\Delta\phi_{i,t}^{IV} \equiv \phi_{i,t}^{IV} - \phi_{i,t-1}^{IV}, \tag{5}$$

$$\phi_{i,t}^{IV} \equiv -\frac{I_{China\rightarrow non-Japan,i,t}}{S_{Japan,i,1996}}. \tag{6}$$

As in the case of the Leontief inverse matrices, we fix the year of market size in 1995. This instrument has the advantage of not being directly affected by changes in productivity in the Japanese industries.

We also construct the instrumental variables for $\Delta\phi_{i,t}^{downstream}$ and $\Delta\phi_{i,t}^{upstream}$ by using the same procedure based on the input-output table:

$$\Delta\phi_{i,t}^{upstream,IV} \equiv \phi_{i,t}^{upstream,IV} - \phi_{i,t-1}^{upstream,IV}, \tag{7}$$

$$\phi_{i,t}^{upstream,IV} = \sum_j M_{i\rightarrow j}^{output,1996}\phi_{j,t}^{IV}. \tag{8}$$

$$\Delta\phi_{i,t}^{downstream,IV} \equiv \phi_{i,t}^{downstream,IV} - \phi_{i,t-1}^{downstream,IV}, \tag{9}$$

$$\phi_{i,t}^{downstream,IV} = \sum_j M_{j\rightarrow i}^{input,1996}\phi_{j,t}^{IV} \tag{10}$$

The result of first stage regression is shown in Table 2 and the related summary statistics in Table 3.

2.2 Data

Our industry level data come from the Research Institute of Economy, Trade and Industry (RIETI) Japan Industrial Productivity Database (JIP Database), Growth Accounting. Throughout our industry-level analysis, we focus on real value added as our measure of output. We utilize the data for years 1996 to 2009. Using the first year's data as a baseline, we cover 13 changes from 1996 -1997 to 2008 - 2009. JIP

Database has 108 industries in total. Since we use only manufacturing industries, we have 50 observations each year and hence 650 observations in total. The data for constructing China import shocks again come from the RIETI JIP Database. Further details of the data are described in the online appendix.

2.3 Results of the industry-level instrumental variable estimation

The main estimated using instrumental variables (Equation 1) is

$$\Delta \ln y_{i,t} = \eta_t + \psi \Delta \ln y_{i,t-1} + \beta^{own} \triangle \phi_{i,t-1} + \beta^{up} \triangle \phi_{i,t-1}^{upstream} + \beta^{down} \triangle \phi_{i,t-1}^{downstream} + \epsilon_{i,t}, \tag{11}$$

repeated there for the reader's convenience.[8]

The first column of Table 1 shows the main results of the industry-level analysis. In agreement with economic intuition, upstream effects, which come from Chinese-productivity-driven trade shocks to an industry's customers, have a (strong) negative effect on the real value added of that industry. This is analogous to the finding by Acemoglu, Akcigit and Kerr (2015b) for the case of the United States. Recall that an increase in imports from China corresponds to a positive value of the shocks, and thus negative coefficients imply that increasing imports from China reduce value added growth in the affected industries. Downstream effects are of positive and significant, which disagrees with Acemoglu, Akcigit and Kerr (2015b)'s model and their empirical results for the United States. Positive downstream effects are, however, consistent with economic intuition: Japanese firms are likely to gain if China becomes more productive in their supplier industry (or industries).

[8] As we discuss in Appendix A, according to the model of Acemoglu, Akcigit and Kerr (2015b), the Chinese productivity-driven shock should have greater upstream effects than downstream effects.

The estimated coefficients are quite large. Note that in the firm-level analysis analogous coefficients turn out to be smaller. Although it is not relevant to our main analysis, the coefficient on lagged dependent variable is negative, showing that strong mean reversion in real value added. The mean reversion may be due to agricultural industries. When we drop agricultural industries from our baseline analysis, the coefficient on the lagged variable is positive and insignificant.

The second column of Table 1 shows the results of the ordinary least squares estimation for completeness. Table 2 and Table 3 present the coefficients in the first-stage regressions and summary statistics respectively.

3 Firm-level analysis of productivity shock propagation

The empirical results of the aggregate-level regression tell us that Chinese-productivity-driven import shocks have stronger (positive) downstream effects than (negative) upstream effects, in contrast to the analysis in the U.S. In this section we perform a firm-level analysis, which is likely to be more reliable, given that we can use industry fixed effects and given that we can incorporate the effects of firm size.

3.1 Firm data

The firm-level datasets were created by Tokyo Shoko Resarch, Ltd (TSR) and provided to us by the Research Institute of Economy, Trade and Industry (RIETI). The firm outcome data comes from the TSR Company Information Database 2006, 2007, 2011, and 2012 and the network data from TSR Company Linkage Database 2006, 2007, 2011, and 2012. In some cases the outcome data also contained one- or two-year lags of firm variables. The number of the firms contained varies across years. The database provides information on firm characteristics and supplier-customer relationships. Firm characteristics data contain each firm's industry code, sales, profits, the number of employees, etc. The supplier-customer relationship data report the firm's suppliers, customers, and major shareholders. For each firm, there are up to 24 transaction partners listed for each category.

3.2 Empirical strategy for the firm-level instrumental variable estimation

In our baseline estimation, we use a firm-level version of the instrumental-variable regression equation that we used in the aggregate-level analysis:

$$\triangle \ln y_{i,t} = \psi \triangle \ln y_{i,t-1} + \beta^{own} \triangle \varphi_{i,t-1} + \beta^{upstream} \triangle \varphi^{upstream}_{i,t-1} + \beta^{downstream} \triangle \varphi^{downstream}_{i,t-1} + \varepsilon_{i,t}. \tag{12}$$

There are two main differences: First, we use either firm sales or profit margin for $y_{i,t}$.[9] Second, we do not use Leontief inverse matrices and instead compute $\varphi^{upstream}_{i,t}$ and $\varphi^{downstream}_{i,t}$ as follows:

$$\triangle \varphi^{downstream}_{i,t} \equiv \frac{1}{n_{suppliers}} \sum_{j \in suppliers(i)} w_j \triangle \varphi_{j,t},$$

$$\triangle \varphi^{upstream}_{i,t} \equiv \frac{1}{n_{customers}} \sum_{j \in customers(i)} w_j \triangle \varphi_{j,t},$$

$$\triangle \varphi_{j,t} \equiv \varphi_{j,t} - \varphi_{j,t-1},$$

[9]Although our dependent variables are different from the model and estimation in Acemoglu et al. (2015b), they seem to be reasonable. Since the model assumes technologies do not change by demand shocks, prices of goods do not change. Hence revenue (sales) would not change if outputs remain unchanged. Therefore we use revenue (sales) and profit margin as proxies of output.

$$\varphi_{j,t} \equiv - \sum_{\alpha \in industries(j)} \tilde{w}_\alpha \frac{I_{China \to Japan,\alpha,t}}{S_{Japan,\alpha,2005}}.$$

The variable $\triangle\varphi_{i,t}^{upstream}$ ($\triangle\varphi_{i,t}^{downstream}$) represents shocks to industries to which customer firms (supplier firms) belong. We do not use the Leontief inverse matrices because when looking closer at the aggregate-level regression, we concluded that it made almost no difference when we excluded indirect effects (such as industry 1 affecting industry 2 that in turn affects industry 3, etc.), so using the full inverse is an unnecessary complication. As in the aggregate-level analysis, we use the eight non-Japan OECD countries' import value from China to construct instrumental variables for $\triangle\varphi_{i,t}$, $\triangle\varphi_{i,t}^{upstream}$ and $\triangle\varphi_{i,t}^{downstream}$.[10] The weights w_j are indicator variables introduced because of data limitations: w_j equals 1 if we have information on firm j, and 0 otherwise. The weights $\tilde{w}_\alpha$ reflect the weights of industries α associated with firm j via a concordance table, as described below.

The value of imports is calculated based on data from the UN Comtrade database, which reports trade values for industries classified by codes of the Standard International Trade Classification (SITC), Revision 3. We used concordance tables in Eurostat provided by European Commission to transform the data to ISIC, Revision 3 codes for manufacturing industries. If a code in one classification corresponded to multiple codes in the other classification, we split the trade values evenly between those multiple codes, in order to avoid over-counting.

We processed in a similar way the values of exports, which were needed to calculate the market size. The market size calculation required also the value of output of Japanese industries. These were obtained from the United Nations Industrial Development Organization (UNIDO) database in the ISIC, Revision 3 classification and converted from Japanese yen to US dollars using the corresponding exchange rate

[10]Note that we use $S_{Japan,i,2005}$ for the denominator in constructing IV of $\varphi_{i,t}$.

reported by the UN Comtrade database.

To assign firms to industries, we use the firms' Japan Standard Industrial Classification (JSIC), Revision 11 codes reported by Tokyo Shoko Resarch, Ltd (TSR). Converting these codes into ISIC, Revision 3 codes is a non-trivial task, since no detailed official concordance between these classifications exists. In order to create a map between the industry codes, we used both other existing concordances and manual matching. In particular, we first linked the codes using concordance tables from JSIC, Revision 11 to JSIC, Revision 12; from JSIC, Revision 12 to JSIC, Revision 13; and from JSIC, Revision 13 to ISIC, Revision 4. These tables were provided by the Japanese Ministry of Internal Affairs and Communications. Further we connected ISIC, Revision 4 codes to ISIC, Revision 3 codes using a concordance table in Eurostat provided by European Commission. In this way each JSIC, Revision 11 was linked to ISIC, Revision 3 codes. This procedure resulted in quite many ISIC, Revision 3 codes for each JSIC, Revision 11, since the concordances were often one-to-many mappings. In order to keep only reasonable matches, we inspected the resulting ISIC, Revision 3 codes corresponding to each JSIC, Revision 11 and deleted those that were unrealistic. We used the resulting corrected concordance to assign ISIC, Revision 3 codes to the firms in our dataset. If a firm j is associated with n_j ISIC, Revision 3 codes, then $\tilde{w}_\alpha$ equals $1/n_j$ for each of these industries α.

For constructing the firm network, we used the business relationship data from year 2006. To identify suppliers and customers of a firm, we use both the information reported by the firm and the information reported by its business partners. Further details of the data are again described in the online appendix.

3.3 Results of the firm-level instrumental variable estimation

In the sample for the baseline regression we only include firms that report at least one non-zero output (or profit margin) change to avoid noise due to reporting inertia. For the shock downstream and upstream variables, we exclude firms that have all suppliers and customers in the same industry.

Table 4 reports the result for our baseline firm-level regression. The first column shows the results for our baseline firm-level instrumental variable regression that includes the first lag of log revenue change as a control variable. Due to data availability, the sample years are 2006, 2007, 2011, and 2012, for which we could calculate the log revenue change as well as its first lag. The estimated own effect (corresponding to $\Delta\phi$) is negative and significant (here we consider 5% as the default significance level). The interpretation of the coefficient is that a one percent Chinese-productivity-driven increase of import penetration ratio in the industry in which the firm belongs to decreases the firm sales by 1.1%. Similar intuitive interpretation of magnitudes applies to the firm network effects discussed below.

Consistent with our aggregate-level analysis, the downstream effect (corresponding to $\Delta\phi^{downstream}$) is positive and significant. The magnitude of the downstream effect is larger than that of the own effect, suggesting strong propagation through firm networks. The sign of the coefficient is intuitive: Japanese firms benefit if China becomes more productive in their supplier industries, making it easier to get cheaper or higher-quality inputs. The upstream effect (corresponding to $\Delta\phi^{upstream}$) is negative and significant. The sign is again intuitive: Japanese firms are negatively affected if China becomes more productive in their customer industries, intensifying competition there. Lastly, the coefficient for lagged dependent variable is negative and significant. We observe that the degree of mean reversion is much smaller than that of aggregate-level analysis.[11]

The second column of Table 4 shows the results for a more detailed firm-level instrumental variable regression that includes as control variables the first two lags of log revenue change, as well as interactions with log revenue in the initial year 2006. The reason for including the interaction terms is that we found the degree of mean reversion to depend on the firm size. This is intuitive: for small firms one-time to revenue have a large relative impact on overall revenue, whereas for large firms with many customers and/or many product lines, multiple one-time shocks to revenue often average out and have a small relative impact on overall revenue. Due to data availability the sample years are 2007 and 2012, as we needed an additional year of revenue data to calculate the two-year lag of revenue change. This regression includes industry fixed effects, in addition to year fixed effects.

The main coefficients of interest have signs and significance levels consistent with those in the baseline regression: the downstream effect is still positive and significant, and the upstream effect is again negative and significant. Their magnitude is larger than for the baseline regression. The estimated own effect turns out to be statistically insignificant.[12] The revenue growth mean reversion coefficients and their interactions with firm size have the intuitive signs and are significant at least at the 10% level. The R^2 of the regression is 0.09, which is quite large given that firms are subject to substantial idiosyncratic revenue shocks and given that this is an instrumental variable regression.

Our data allowed us to perform similar estimation for the firms' profit margin, with the results reported in Table 5. The profit margin is defined here as the ratio

[11] The first-stage results of this baseline regression are reported in Table 6. Note that our IVs are not weak IVs.

[12] The reduction in significance is not completely surprising, given that there are many industry fixed effect included in this regression.

of the firm's profit to the firm's revenue. Note that here we use levels of the profit margin, unlike in the case of the revenue regression, where we used logarithms of revenue. The sample years are 2006, 2007, 2011, and 2012. We include the one-year lag of profit margin growth and its interaction with revenue-based log firm size as control variables. Unlike in the case of the revenue regression, two-year lags would not be significant here and are not included, as profits are volatile and typically hard to predict two years in advance. The profit margin regression includes both year fixed effects and industry fixed effects.

We see a positive and significant coefficient for the downstream effect. The magnitude of the effect of downstream propagation is quite large. Intuitively, it implies that if due to increased Chinese productivity the import penetration ratio increases by one percent in the industry to which the firm's suppliers belong, then the firm's profit margin increases by 25%. The upstream effect and the own effect have the economically intuitive signs but do not have statistical significance here. The lagged profit margin growth has a large negative and significant coefficient, indicating a large mean-reversion tendency for firms' profit margins. The R^2 of this regression is remarkably large, above 0.5.

Additional regressions and robustness checks are included in the online appendix.

4 Conclusion

This paper empirically investigates the transmission of macroeconomic shocks: the variation in exports from China induced by Chinese productivity changes, and the resulting impact on the Japanese economy. The model of Acemoglu, Akcigit and Kerr (2015b) applied to the case of Japan predicts that when an industry experiences an increase in imports from China due to increased Chinese productivity, supplier industries are affected much more than customer industries, which should be almost unaffected. When the original industry increases the import from China, more Chinese goods in that industry are in the Japanese market, and then the demand for the goods produced by Japanese firms is reduced. The original industry adjusts its production levels, and thus reduces input demands, which is the source of negative effects on supplier industries. On the other hand, customer industries are less affected because the shocks have much more minor effects on prices. Acemoglu, Akcigit and Kerr (2015b) use the U.S. industry-level data and find the propagation of shocks to imports from China through input-output linkages with a pattern consistent with their model.

We first use the Japanese input-output table data to construct industry-level networks and test how upstream and downstream industries are affected when an original industry experiences the rise in the imports from China. Following Autor, Dorn and Hanson (2013a), we use instrumental variable estimators to identify the exogenous component of the variation in imports from China. We found significant negative upstream effects, implying that supplier industries reduce their output when the original industry gets hit by shocks in the form of increased import from China. However, unlike Acemoglu, Akcigit and Kerr (2015b), downstream effects turn out to be positive and significant in our analysis. These positive downstream effects imply that the customer industry increases its outputs even when the original industry suffers output losses by more intense competition with Chinese goods. Also, the magnitude of network-based propagation (upstream and downstream effects) is larger than the direct effects of the shocks, indicating that the transmission of shocks through industry-level networks could have a substantial impact on the macroeconomy.

We performed a similar analysis using firm-level networks. We found significant positive downstream effects and significant negative upstream effects for the impact on firms' revenue. We also found a positive and sizable downstream effect for that on firms' profit margin. The firm-level analysis is more reliable since we could use industry fixed effects and incorporate the effects of firm size.

Overall, our industry- and firm-level results suggest that shocks in the form of variation in imports from China are strongly transmitted through industry and firm networks and have large effects on the Japanese economy.

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Appendix

A Theoretical background of industry-level analysis

Our industry-level regression is motivated by the theory part of Acemoglu, Ozdaglar and Tahbaz-Salehi (2015a). They found that industry level-shock propagation based on the input-output linkage had a significant impact on the economy. The notation in this appendix is taken from Acemoglu, Ozdaglar and Tahbaz-Salehi (2015a), which the reader may consult for details.

Based on the models in Long Jr and Plosser (1983) and Acemoglu, Ozdaglar and Tahbaz-Salehi (2015a), they built a multi-sector model which describes a relationship between firm performance and the direct and indirect impact of the macroeconomic shocks. They employ the setting of perfect competition, a Cobb-Douglas production function and Cobb-Douglas consumer preferences. Specifically, in their model, a production function of each industry i takes the form of

$$y_j = e^{z_j} l_j^{\alpha_j^l} \prod_{i=1}^{n} x_{ji}^{a_{ji}},$$

where x_{ji} is the quantity of goods produced by industry i used as inputs by industry j, l_j is labor in industry j, and z is Hicks-neutral productivity shock. The fixed parametersα and a satisfy $\alpha_j^l + \sum_{i=1}^{n} a_{ji} = 1$ to ensure constant returns to scale.

The utility function of a representative household is

$$u\left(c_1, c_2, \cdots, c_n, l\right) = \gamma\left(l\right) \prod_{i=1}^{n} c_i^{1/n},$$

where c_j is the final consumption of the output of industry j and $\gamma(l)$ captures disutility of labor supply. In this economy the government imposes a lump-sum tax: $T = \sum_{i=1}^{n} p_i G_i$, where p_i is the price of the goods produced by industry i and G_i are the government purchases of good i, which do not directly affect the representative household's utility.

After expressing supply-side shocks (e.g., productivity shocks) and demand-side shocks (e.g., shocks to government purchases) by using the Leontief inverse matrix, their model yields the following equation for the full impact on output in sector i from a supply-side shock:

$$d \ln y_i = h_{ii} \times dz_i + \sum_{j \neq i} h_{ij} \times dz_j,$$

and the full impact on output in sector i from a demand-side shock:

$$d \ln y_i = \underbrace{\hat{h}_{ii} \times (1 - \Gamma) \times \frac{dG_i}{p_i y_i}}_{\text{own effect}} \underbrace{- \Gamma \times \sum_{j \neq i} \hat{h}_{ji} \times \frac{dG_j}{p_i y_i}}_{\text{network effect}}.$$

Their model shows that there is a strong connection between the direct impact of the exogenous shock on a particular sector and the indirect effect of the shock to the other sectors, propagated through a network of input-output linkages. In addition, we can see that the supply-side shocks do not propagate upstream and the demand-side shocks (almost) do not propagate downstream. Their empirical tests conclude that the propagation based on the input-output network is larger than the direct effect of the shocks on a particular industry. This suggests the importance of the idea that a shock to a single sector could have a large impact on the macroeconomy, which is also suggested in previous work such as Gabaix (2011).

B Tables

Table 1: Industry-level instrumental-variable estimation (1) and ordinary least squares estimation (2).

	(1) $\Delta \log y_t$	(2) $\Delta \log y_t$
$\Delta\phi$	-8.121	-14.36**
	(24.20)	(7.312)
$\Delta\phi^{\text{downstream}}$	30.07**	20.19***
	(14.50)	(7.324)
$\Delta\phi^{\text{upstream}}$	-14.12**	-5.600
	(6.875)	(4.832)
$\Delta \log y_{t-1}$	-0.904***	-0.901***
	(0.0506)	(0.0505)
Year fixed effects	Yes	Yes
Observations	650	650
R^2	0.335	0.346

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2: Industry-level first-stage regressions

	(1) $\Delta\phi$	(2) $\Delta\phi^{\text{downstream}}$	(3) $\Delta\phi^{\text{upstream}}$
$\Delta\phi^{\text{IV}}$	-0.005	-0.028***	-0.030***
	(0.003)	(0.004)	(0.004)
$\Delta\phi^{\text{downstream,IV}}$	0.009**	0.032***	0.008*
	(0.004)	(0.004)	(0.004)
$\Delta\phi^{\text{upstream,IV}}$	0.001	0.002	0.028***
	(0.002)	(0.003)	(0.003)
Constant	0.003***	0.004***	0.005***
	(0.001)	(0.001)	(0.001)
Observations	650	650	650
R^2	0.139	0.273	0.336

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3: Means and standard deviations of industry-level variables

	(1) Total
$\Delta \log y_t$	-.0149
	(0.4908)
$\Delta\phi$	0.0037
	(0.0086)
$\Delta\phi^{\text{downstream}}$	0.0058
	(0.0109)
$\Delta\phi^{\text{upstream}}$	0.0067
	(0.0119)
$\Delta\phi^{\text{IV}}$	0.1220
	(0.3110)
$\Delta\phi^{\text{downstream,IV}}$	0.1873
	(0.3630)
$\Delta\phi^{\text{upstream,IV}}$	0.2055
	(0.3737)
Observations	650

Standard errors in parentheses

Table 4: Firm-level instrumental-variable estimation for revenue.

	(1) $\Delta \log y_t^{\text{revenue}}$	(2) $\Delta \log y_t^{\text{revenue}}$
$\Delta\phi$	-1.064**	0.300
	(0.437)	(1.744)
$\Delta\phi^{\text{downstream}}$	1.408**	4.943**
	(0.711)	(2.178)
$\Delta\phi^{\text{upstream}}$	-0.888**	-1.922**
	(0.443)	(0.957)
$\Delta \log y_{t-1}^{\text{revenue}}$	-0.192***	-0.180***
	(0.010)	(0.037)
$\Delta \log y_{t-2}^{\text{revenue}}$		-0.051**
		(0.024)
$\Delta \log y_{t-1}^{\text{revenue}}(\log y_{2006}^{\text{revenue}})^{\star}$		0.038**
		(0.019)
$\Delta \log y_{t-2}^{\text{revenue}}(\log y_{2006}^{\text{revenue}})^{\star}$		0.020*
		(0.010)
Constant	0.086***	
	(0.007)	
Year fixed effects	Yes	Yes
Industry fixed effects	No	Yes
Observations	9194	4557
R^2	0.0543	0.0931

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(1) We only use firms who report at least some output change.

Note: An interaction term $\Delta \log y_{t-1}^{\text{revenue}}(\log y_{2006}^{\text{revenue}})^{\star}$ that appears in the table is an abbreviation for the precise expression $\Delta \log y_{t-1}^{\text{revenue}}\left(\log y_{2006}^{\text{revenue}} - \overline{\log y_{2006}^{\text{revenue}}}\right)$, where $\overline{\log y_{2006}^{\text{revenue}}}$ is the mean log revenue in 2006. Similarly for $\Delta \log y_{t-2}^{\text{revenue}}(\log y_{2006}^{\text{revenue}})^{\star}$.

Table 5: Firm-level instrumental-variable estimation for profit margin

	(1) $\Delta y_t^{\text{profit margin}}$
$\Delta\phi$	-7.574
	(12.476)
$\Delta\phi^{\text{downstream}}$	25.989***
	(9.311)
$\Delta\phi^{\text{upstream}}$	-9.281
	(5.729)
$\Delta y_{t-1}^{\text{profit margin}}$	-0.673***
	(0.170)
$\Delta y_{t-1}^{\text{profit margin}}(\log y_{2006}^{\text{revenue}})^{\star}$	-0.039
	(0.038)
Year fixed effects	Yes
Industry fixed effects	Yes
Observations	9093
R^2	0.513

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(1) We only use firms who report at least some output change.

Note: An interaction term $\Delta y_{t-1}^{\text{profit margin}}(\log y_{2006}^{\text{revenue}})^{\star}$ that appears in the table is an abbreviation for the precise expression $\Delta y_{t-1}^{\text{profit margin}}\left(\log y_{2006}^{\text{revenue}} - \overline{\log y_{2006}^{\text{revenue}}}\right)$, where $\overline{\log y_{2006}^{\text{revenue}}}$ is the mean log revenue in 2006.

Table 6: Firm-level first-stage regressions

	(1)	(2)	(3)
	$\Delta\phi$	$\Delta\phi^{\text{downstream}}$	$\Delta\phi^{\text{upstream}}$
$\Delta\phi^{\text{IV}}$	14.671***	0.123	0.169
	(0.417)	(0.251)	(0.374)
$\Delta\phi^{\text{downstream,IV}}$	-0.267	19.045***	1.346*
	(0.869)	(0.524)	(0.779)
$\Delta\phi^{\text{upstream,IV}}$	0.105	0.625**	17.808***
	(0.505)	(0.304)	(0.452)
Constant	0.003***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)
Observations	9194	9194	9194
R^2	0.139	0.169	0.189

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Summary statistics for firm data in 2006

	Mean	Median	Std. Dev.	Min	Max	N
Revenue	12,412,000	2,114,000	45,204,000	9,000	965,866,000	2603
Log Revenue	14.67	14.56	1.801	9.105	20.69	2603
Profit	393,800	35,370	1,874,000	4	64,559,000	2236
Employment	240.2	75	645.3	1	12,850	2606
Log Employment	4.336	4.317	1.484	0	9.461	2606

We calculate summary statistics for the firms we use in our baseline regression: this table includes the firms who report more than one change in its production, non-zero revenue and non-zero profit.