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Demand Shock Propagation Through an Input-output Network in Japan

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Abstract

Recent studies (e.g., Acemoglu et al (2012)) show that micro-level shocks propagate through an input-output network and result in aggregate fluctuations. While most previous studies report the propagation of shocks from upstream, we know little about how shocks propagate from downstream. Focusing on the sharp decline in exports from Japan during the global financial crisis and in consumption of food and accommodation services during the COVID-19 pandemic, we empirically examine how these demand shocks propagate from customers to suppliers through a firm-level input-output network. We find that the propagation of demand shocks depends on firm size and, in particular, on the mutual importance of the transaction relationship. For the case of the global financial crisis, negative demand shocks propagate from large exporters to larger suppliers because they regarded each other as their main transaction partners. In contrast, while small suppliers regarded these large exporters as their main partners, larger exporters do not see the small suppliers that way, and thus, the propagation via these transaction relationships is limited. For the case of the pandemic, negative demand shocks are transmitted from small customers even to their small suppliers. This is because many suppliers of firms that belong to pandemic-affected sectors are small, yet they are viewed as the main transaction partners by their customers. These results suggest that the mutual importance of transaction relationships determines the heterogeneity of the demand-shock propagation.

Keywords: Input-output network; Propagation of demand shocks; Heterogeneous treatment effect

JEL classification: E32, E23, D57

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1 Introduction

Propagation of shocks via input-output linkages between firms has gained attraction among economists. Recent theoretical analysis (e.g., Acemoglu et al. (2012)) shows that microeconomic shocks to hub firms in an input-output network have a large impact on aggregate output. Furthermore, because of the increasing availability of firm-level data, recent empirical studies have directly analyzed such firm-level input-output network and found propagation phenomenon (e.g., Barrot and Sauvagnat (2016), Boehm et al. (2019); Carvalho et al. (2021)). However, most of the previous studies focus on propagation driven by supply shocks such as earthquakes and hurricanes, that is, shocks propagate downstream from supplies to customers. In contrast, propagation from customers to suppliers driven by demand shocks is rarely examined in the empirical literature. Although both downstream and upstream propagations could be important as the transmission channels of shocks, we know little about the latter.

This paper aims to fill this gap in the literature using Japanese firm-level input-output data. We focus on demand-shock propagation originating from a sharp drop in exports during the global financial crisis and change in consumer behavior during the COVID-19 pandemic. By viewing these events as exogenous to Japanese firms, we examine how the sales growth rates of firms are affected according to whether their transacted customers experience these negative shocks. In methodology, we use the heterogeneous treatment effect model developed by Athey et al. (2019) and Wager and Athey (2018), which enables us to analyze how the propagation effect depends on firms' characteristics, for example, firm size. By focusing on the heterogeneity of the propagation effect, we examine the route of the demand-shock propagation on the input-output network.

Our analysis shows that during the global financial crisis, the propagation effect is substantial for large suppliers but not for small suppliers, that is, negative shocks hitting exporting firms are not transmitted to their small suppliers, especially when the exporting firms are large. Although the exporting firms facing the decline in exports reduce inventories, the sales growth rates of their small suppliers, who report the exporting firms as main customers, do not respond to the negative growth rates of these exporting firms. This is because the propagation effect is not homogenous across suppliers, and in particular, demand shocks propagate from customers to suppliers only when their suppliers are the major suppliers for the customers. (see **Figure 1**). Even when the main customers of a supplier experience a large decline in exports, that is, the customers are viewed as major ones from the supplier's viewpoint, as far as this supplier is not viewed as the major one from its customers' viewpoint, the negative shocks hitting the customers are not transmitted to the supplier. In addition, we find the strong dependence between this mutual relationship and the sizes of both firms, that is, large suppliers are likely to be chosen as main suppliers, especially for large customers. Since most of exporting firms and their main suppliers are large firms, demand-shock propagation mainly occurs within large firms during the global financial crisis.

The finding about the heterogeneity of the propagation effect raises another question: if demand shocks

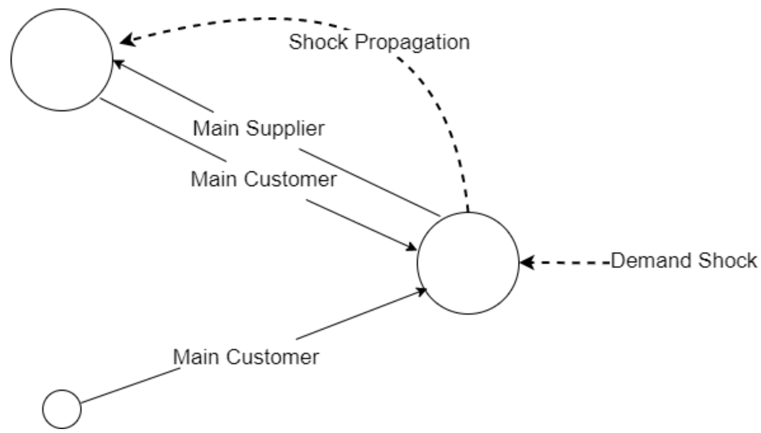


Figure 1: Route of the demand-shock propagation. The size of the circle represents the size of the firm. Demand shocks propagate to its suppliers only when the suppliers are main suppliers for the customer. In particular, the propagation of demand shocks does not occur between large customers and small suppliers.

hit firms which has small suppliers as main ones, the negative shocks propagate to the small suppliers? Our analysis shows that this is what happened during the COVID-19 pandemic. The most of firms belonging to the COVID-affected sectors such as restaurants and hotels are small, and their main suppliers also small. Applying the same method as in the case of the global financial crisis, we find that there is no significant heterogeneity of the propagation effect across the size of suppliers. That is, negative demand shocks propagate even to small suppliers as well. This result gives another support for our interpretation that propagation occurs only through the linkages which are relevant to both supplier and customer.

Our analysis suggests that there exists links through which demand shocks tend to propagate and links though which demand shocks cease to propagate. In other words, by connecting the former links in an input-output network, we are able to identify the route of the demand-shock propagation. The identification of the propagation route is important not only academically but also of relevance to policymakers because we can assess the effect of policy measures such as subsidies to targeted firms more precisely (see e.g., Liu (2019)). Our finding can be viewed as the first step for this purpose.

Related literature

This paper belongs to the literature on the micro-origin of aggregate fluctuations, in which the propagation of microeconomic shocks on an input-output network has been analyzed (for a survey, see Carvalho (2014) and Carvalho and Tahbaz-Salehi (2019)). An influential study by Acemoglu et al. (2012) considers the structure of an input-output network explicitly and proposes a general equilibrium model describing the propagation of productivity shocks on the network. This model has been the theoretical foundation for subsequent studies (e.g., Baqaee and Farhi (2020b);Baqaee and Farhi (2019);Bigio and La'o (2020);Liu (2019)). Although supply shocks are considered in most of the previous studies, demand shocks are also examined by some recent papers (Shea (2002); Kramarz et al. (2020); Herskovic et al. (2020)). In particular, Herskovic et al. (2020) provide a theoretical counterpart to Acemoglu et al. (2012) for the demand-shock propagation.

Although these studies above clarify the importance of the network structure, it is implicitly assumed that the propagation of microeconomic shocks is homogeneous across firms. Intuitively, because of this assumption, the impact of microeconomic shock to a firm is proportional to the number of links (i.e., transaction relationships) that the firm has (see Acemoglu et al. (2012)). Since it is known that large firms have transactions with many small suppliers and/or customers, that is, negative degree assortativity (see, e.g., Bernard and Moxnes (2018);Bernard et al. (2014);Lim (2018);Bernard et al. (2019)), it turns out that large firms lie at the center of the network, and thus, shocks hitting these large firms propagate across an economy. In contrast, our finding suggests that the role of large firms in the demand-shock propagation is limited compared to that predicted by the previous studies because the demand-shock propagation does not occur through these links between large customers and small suppliers. That is, demand shocks hitting large firms are transmitted only to their large suppliers and do not spread across an economy.

In empirical perspective, our paper is closely related to studies which use a natural disaster as an exogenous shock. Barrot and Sauvagnat (2016) use the natural disasters damaging firms in the US economy as the source of negative productivity shocks and examine the propagation of this shock via firm-level input-output linkages. In particular, they show that the specificity of inputs that the damaged firm supplies is crucial for the downstream propagation of the shocks. Boehm et al. (2019) and Carvalho et al. (2021) use the Tohoku earthquake in Japan in 2011 as the source of negative productivity shocks and test if this negative shock propagates to other customers located in unaffected regions. In contrast, empirical studies focusing on demand shocks are sparse in the literature. The exception is Acemoglu et al. (2016) and Kisat and Phan (2020), which analyze the propagation of demand shocks using a sector-level input-output network.[1] To the best of our knowledge, there is no empirical study which directly observes the demand-shock propagation at the firm-level input-output linkages.[2] In addition, our paper is the first attempt to capture the heterogeneity

[1] Focusing on a policy change in India (demonetization of its currency), Kisat and Phan (2020) attempt to detect the demand-shock propagation but argue that the negative shock does not propagate through the network. In their analysis, although outcome variables such as revenue and investment are at the firm-level, the position of a firm on the network is approximated by the upstreamness measure, which is estimated by a sector-level input-output network. In contrast, the input-output network in our analysis is also at the firm-level, which gives us more statistical power to detect the demand-shock propagation.

[2] Another type of shock propagation has been studied in related literature. For example, the examination about credit supply by bank and/or firms and its spillover effect on an input-output network forms an important field of research (Jacobson and Von Schedvin (2015);Amiti and Weinstein (2018);Luo (2020);Dwenger et al. (2020);Costello (2020);Huremovic et al. (2020);Alfaro et al. (2021)). Related to these studies above, some recent papers focus on monetary shocks and their propagation on an input-output network (e.g., Auer et al. (2019);Adelino et al. (2020);Di Giovanni and Hale (2021);Pasten et al. (2020);Jennifer and Tahbaz-Salehi (2020);Mandel et al. (2019)).

of the propagation effect according to firms' characteristics.[3] Thus, our paper complements the empirical literature by finding an economically significant propagation of demand shocks and by identifying the route of the shock propagation on an input-output network.[4][5]

Outline

Our paper is organized as follows. In Section 2, we overview our data used in our analysis. In Section 3, we provide our empirical model to test the heterogeneity of the propagation effect. In Section 4, we give our main empirical results. In Section 5, we conclude.

2 Overview of Data

We overview our firm-level data in Japan. In Section 2.1, we explain how this data is constructed. In Section 2.2, we focus on the period of the global financial crisis. In Section 2.3, we focus on the period of the COVID-19 pandemic.

2.1 TSR Data

The firm-level data used in our analysis is provided by Tokyo Shoko Research (TSR). TSR asks firms in Japan to report their financial information such as industry classification, annual sales revenue, and profits. In particular, these firm individual information includes an export flag, which identifies whether a firm is exporting or not. The export flag is a key variable to identify the firms facing negative demand shocks for the case of the global financial crisis.

[3] Regarding the heterogeneity of the propagation effect, Heise (2019) provide an important finding: the pass-through of exchange rate shocks is more responsive when the transaction relationship is old, that is, a long-term relationship. Although their main focus is on supply shocks and changes in price, the idea that the property of the transaction relationships affects the propagation phenomena is closely related to our finding.

[4] Our paper also contributes to the recent discussion about the propagation of negative shocks caused by the COVID-19 pandemic (e.g., Cerdeiro and Komaromi (2020);Baqaee and Farhi (2020a);Barrot et al. (2020);Ding et al. (2021)). In particular, Cerdeiro and Komaromi (2020) analyze high-frequency shipping data and show that supply shocks caused by lockdown propagate through an input-output network. In contrast, our paper exploits the fact that strong measures such as lockdown has not been taken in Japan but the change in consumers' behavior to reduce the risk of infection is substantial, that is, demand shocks are dominant. Our finding that demand shocks are propagated to small suppliers complement these recent literature by providing another example of the propagation of COVID-related shocks.

[5] For the analysis of the COVID-19 pandemic in Japan, using firm-level input-output data and the model in Acemoglu et al. (2012), Imani et al. (2020) calculate network centrality for each sector and region. They find the significant correlation between the decrease in economic indicator and the degree of network centrality. Different from Imani et al. (2020), our paper directly observes the response of the sales growth rate of a firm to negative shocks hitting to its customers and in particular, does not use the model in Acemoglu et al. (2012) as the basis of our analysis.

Furthermore, our TSR data includes information about input-output linkages between firms. Firms are asked to report their main customers and suppliers up to the top 24 transacted firms for each. For example, by combining the reports about these linkages with the export flag, we can identify which firms are the suppliers of exporting firms. Since our main variable of interest is the sales growth rates of suppliers in response to those of their customers, we focus on the transaction relationships reported by suppliers. That is, these transaction relationships analyzed in our analysis are important from the suppliers' viewpoint. By using these firm-level information, we can identify firms with transacted customers severely damaged by the global financial crisis or the COVID-19 pandemic. Note that these transaction relationships are not necessarily reported by the corresponding customers, that is, a firm reported as a main customer by its supplier may not report the supplier as its main supplier. Such asymmetry relationship is quite common in our data; for example, the number of transaction links reported only from suppliers's sides accounts for more than 90% of the total links reported by suppliers' sides. This point is crucial for the mechanism of the propagation and further discussed in the following sections.

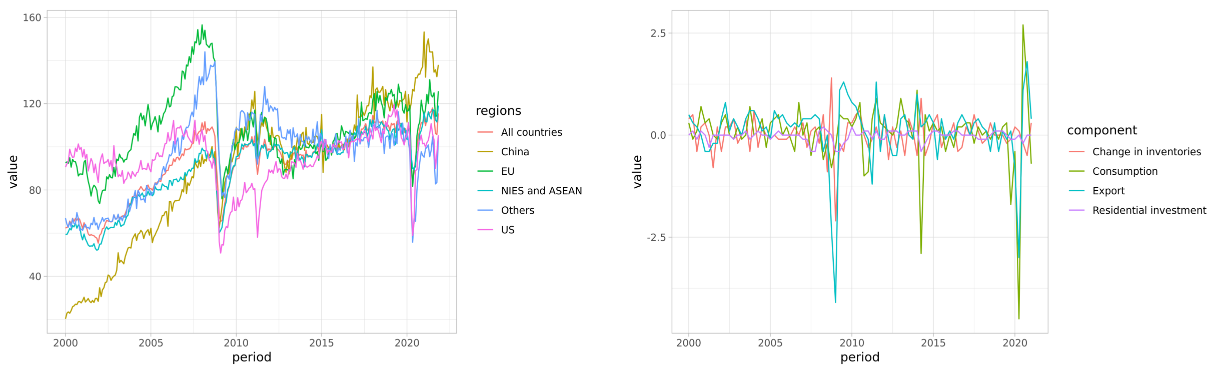
2.2 Global financial crisis

During the period of the global financial crisis (2008-2009), financial institutions across the world incurred huge losses. This crisis reached a climax with the bankruptcy of Lehman Brothers on September 2008, plunging many economies into recession. Although the GDP growth rate of Japanese economy also plummeted during this period, it is known that most of financial institutions in Japan were not damaged because they were not involved in mortgage-backed securities. Negative impacts on Japanese economy came mainly from a sharp drop in exports.[6] **Figure 2** show the time series of exports to different regions (left panel) and of the contribution to the GDP growth rate (right panel).[7] As seen in the left panel, exports from Japan to any region rapidly decrease during this period. This sharp drop in exports seen in the left panel corresponds to that of the contribution of exports to the GDP growth rate in the right panel. Both panels of the aggregate time series show that the sharp drop in exports during this period drove Japanese economy into recession.

Let us check this point using our firm-level data. **Figure 3** provides the histograms of exporting firms, non-exporting firms, and non-exporting firms having at least one exporting customer. As seen in this figure, exporting firms are typically large firms. In contrast, non-exporting firms with at least one exporting firms

[6]This fact has been often mentioned in empirical studies by Japanese economists (e.g., Ando and Kimura (2012);Ogawa and Tanaka (2013);Hosono et al. (2015)). For example, Hosono et al. (2015) point out that the decline in exports in Japan was more severe than in other OECD countries; that is, the decline for Japan is 14.0% and 25.3% for Q4 in 2008 and Q1 in 2009, respectively, while the average of decline is 6.7% and 8.2% for the OECD countries in the two periods.

[7]The time series of export index and contribution to the GDP growth rates are available at Bank of Japan (https://www.esri.cao.go.jp/en/sna/data/sokuhou/files/2021/qe211/gdemenuea.html) and Cabinet Office (https://www.boj.or.jp/en/research/research_data/index.htm), respectively.



(a) Export index (monthly) **(b)** Contribution to the GDP growth rate (quarterly)

Figure 2: Time series of aggregate variables in Japan. In Panel (a), export index is set equal to 100 in 2015. In Panel (b), the three periods that has a sharp drop of some component correspond to the global financial crisis (2008-2009), an increase in VAT (2014), and pandemic (2020-2021).

are not necessarily large firms, which means that small suppliers have transactions with large firms as main customers. Indeed, **Figure 4** shows that the heatmap of the number of transactions links according to the firm sizes of suppliers and customers, suggesting that links between large customers and small suppliers are common. This explains why the average size of the suppliers having at least one exporting customer is small compared to exporting firms, and account for a significant proportion of the non-exporting firms. In the following analysis, the main analysis is the comparison of these non-exporting firms having exporting customers with those having no exporting customers.

To see the impact of the sharp drop in exports on exporting firms, we compare sales growth rates for exporting and non-exporting firms, where the growth rate is defined the log difference of annual sales revenues during this period, that is, $g := \log(\text{sale}_{2009}) - \log(\text{sale}_{2007})$. **Figure 5** compares the density estimates of sales growth rates over these two successive years. This figure shows that the distribution of growth rates for exporting firms is tilted left, and the sample average of growth rates for exporting firms are lower than that of non-exporting firms by about 7%. Consistent with the time series of aggregate variables in **Figure 2**, the exporting firms are more severely damaged by the global financial crisis. This difference of growth rates between exporting and non-exporting firms is used as the source of identification in the following analysis.

Seeing that exporting firms are hit by demand shocks and their suppliers including small (non-exporting) suppliers, let us consider the sales growth rates for non-exporting firms and its dependence on whether their customers are exporting firms or not. As our main samples, we consider non-exporting firms with sales larger than 10 million yen in the manufacturing and wholesale & retail industries. Their summary statistics are given in **Table 1**. To get an initial glimpse of the propagation effect, we consider the dependence of growth rates between the non-exporting firms and their customers.[8] First, consider large suppliers with sales

[8]To be precise, since a supplier may have more than one customers and the weight of each customer (i.e., the transaction volume) is

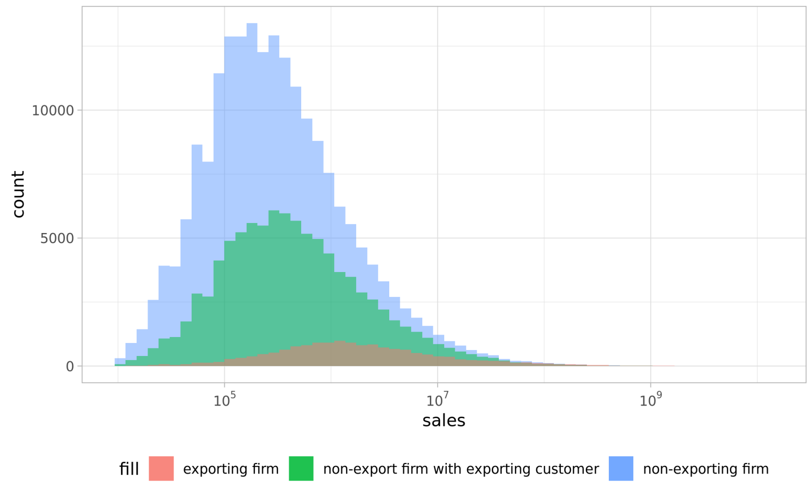


Figure 3: Histograms of firm sales. The unit is thousand yen. For the exporting firms, all industries are considered. The horizontal axis is plotted in the logarithmic scale.

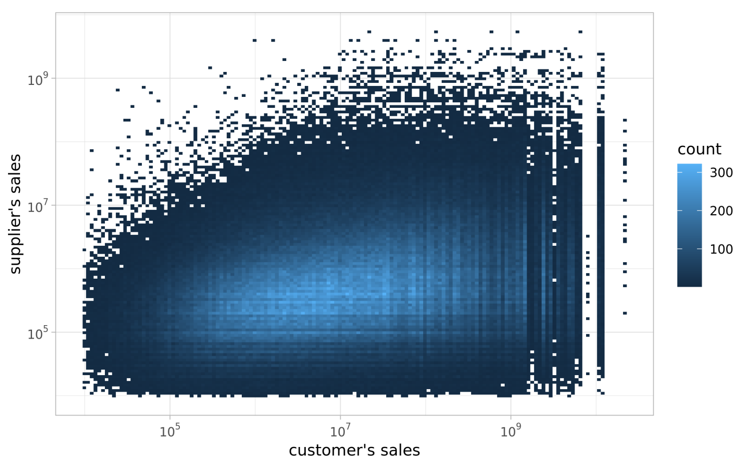


Figure 4: Heatmap of the number of links according to the firm sizes of suppliers and customers. Both axes are plotted in the logarithmic scales.

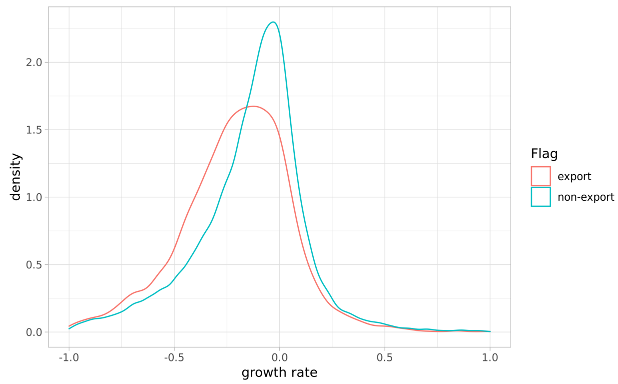


Figure 5: Density estimations of sales growth rates. Since most of exporting firms are large, we restrict our samples to firms with sales larger than 500 million yen for comparison. The mean (median) of growth rates for exporting firms is $-0.206(-0.186)$. The mean (median) of growth rates for non-exporting firms is $-0.136(-0.0967)$.

larger than 5 billion yen. The left-panel of **Figure 6** depicts the heatmap of the two growth rates, showing the high positive correlation (the correlation coefficient $= 0.518$). To identify that this correlation comes from drop in exports, the right-panel of **Figure 6** shows the relation between the growth rate and the fraction of exporting firms among its customers. This figure shows that the two variables are negatively correlated (the correlation coefficient $= -0.243$). As expected, these figures are consistent with the idea that negative shocks are transmitted from their customers via transaction relationships.

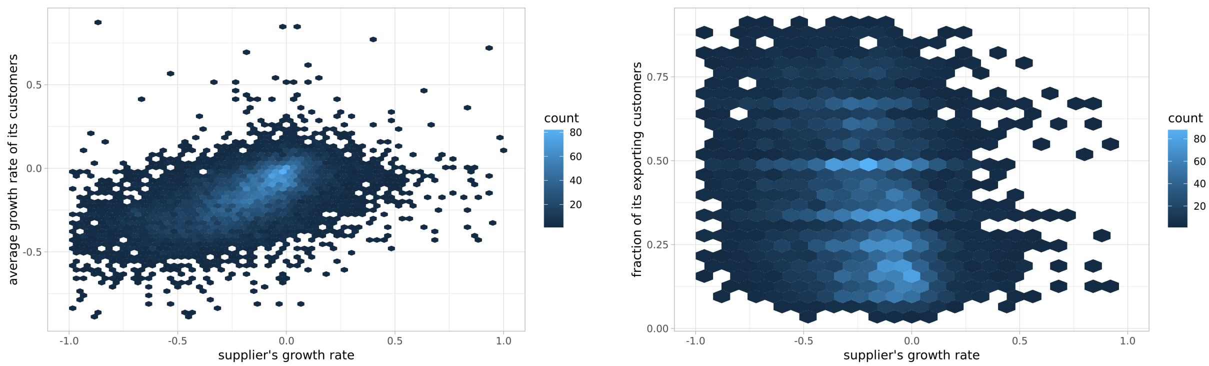
name	count	mean	sd	q1	median	q3
growth rate of supplier	198000	-0.1587	0.2614	-0.2928	-0.1138	-0.0009
log of supplier's sales	198000	12.6403	1.5494	11.5129	12.4684	13.5282
fraction of exporting customers	198000	0.2272	0.3067	0.0000	0.0000	0.4000
average growth rate of its customers	198000	-0.1590	0.1836	-0.2642	-0.1427	-0.0431

Table 1: Summary statistics of non-exporting firms.

However, the dependence of growth rates on those of customers are not observed for small suppliers with sales less than 5 billion yen. **Figure 7**, which depicts the same figure as **Figure 6** but for large firms, shows no clear relationships. Indeed, the correlation coefficients for growth rates between suppliers and customers is 0.244, which is lower than 0.518 for large suppliers, and the correlation coefficient for growth rates and the fraction of exporting customers -0.079. These results suggest that the propagation of demand shocks to suppliers appears to have heterogeneity across firms and, in particular, is economically significant only for large firms during this period.

The most suggestive figure for the identification of the propagation effect is given in **Figure 8**, which

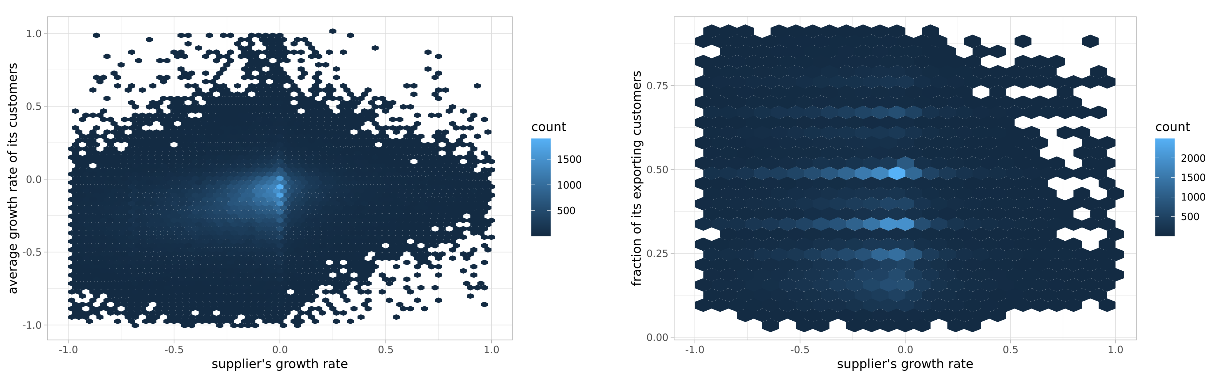
not available, we simply take the sample average of the sales growth rates of its customers. In the following, we mean the sample average by the growth rate of its customers.



(a) with customers' growth rates

(b) with the fraction of exporting firms among its customers

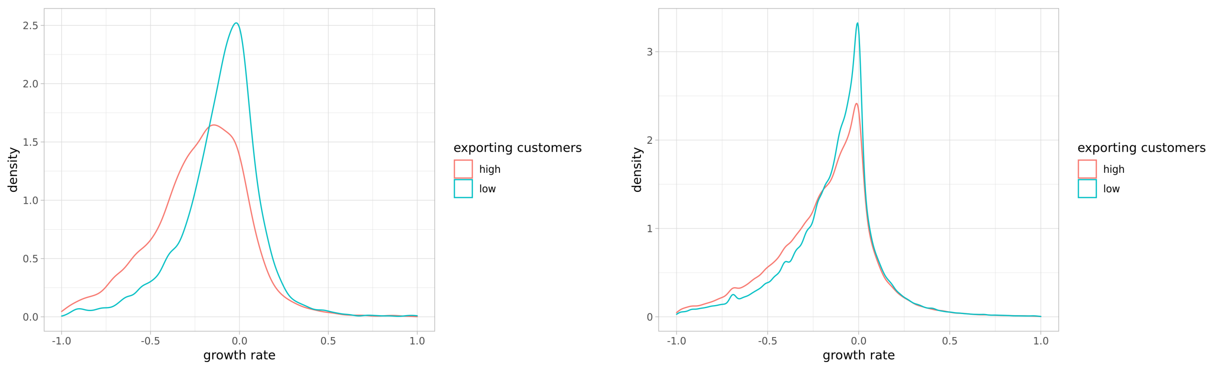
Figure 6: Dependence of sales growth rate. The hexagonal heatmap counts the number of cases in each hexagon and maps it to the hexagon fill. In Panel (b), for presentation purpose, the samples in which the fraction of exporting firms is equal to 0 or 1 are removed here.



(a) with customers' growth rates

(b) with the fraction of exporting firms among its customers

Figure 7: Dependence of sales growth rates for small firms with sales less than billion yen. Others are the same as in **Figure 6**.



(a) Large suppliers

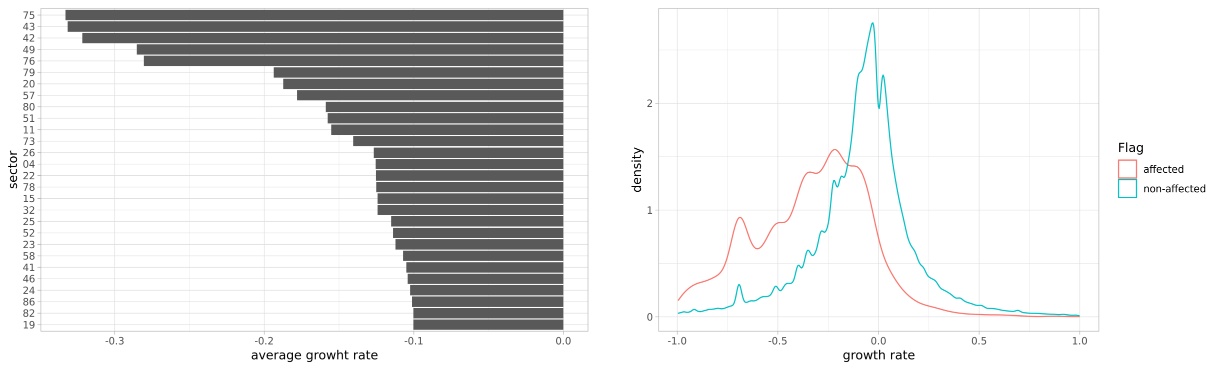
(b) Small suppliers

Figure 8: Density estimation of growth rates for non-exporting firms. Samples are divided by the fraction of exporting firms among its customers (i.e., larger than 0.1 or not) In Panel (a), suppliers with sales larger than 5 billion yen are considered. The mean (median) of growth rates for exporting firms is $-0.224(-0.197)$. The mean (median) of growth rates for non-exporting firms is $-0.105(-0.0726)$. In Panel (a), suppliers with sales less than 5 billion yen are considered. The mean (median) of growth rates for exporting firms is $-0.181(-0.137)$. The mean (median) of growth rates for non-exporting firms is $-0.138(-0.0943)$.

shows the density estimations of sales growth rates for non-exporting firms. In this figure, samples are divided into two groups according to whether the fraction of its exporting customers is larger than 0.1 or not. Since they are non-exporting firms, they are not directly hit by the global financial crisis, that is, a decrease in demand in foreign countries. However, the left-panel of **Figure 8** shows that non-exporting and large suppliers with many exporting customers have lower growth rates by about 12% compared with the non-exporting suppliers with few exporting customers. Thus, negative shocks that originated from foreign countries has reached non-exporting suppliers in Japan via transaction relationships in the case of large suppliers. This feature is not observed for small suppliers as seen in the right-panel of **Figure 8**. The difference between sample averages is about 4%, suggesting that the propagation is not substantial for small suppliers. Consistent with the above discussion, it is necessary to take into account the heterogeneity of the propagation effect across firms.

2.3 COVID-19

In 2020, the COVID-19 pandemic covered the globe and many countries experienced severe economic downturns. Although, similar to other countries, Japanese economy went into recession (see **Figure 2**), one of the features of policy measures in Japan is that the government never takes a strong measure such as lockdown. The major impact on Japanese economy due to this pandemic is change in consumers' behavior: consumers avoided the crowded places such as restaurants, and outdoor/indoor events were cancelled. This is consistent with the right-panel of **Figure 2**, which shows that the major contributor to the decrease in GDP growth rate is private consumption. We regard this change in consumers' behavior as demand shocks and



(a) Mean of sales growth rates

(b) Density estimation of growth rates

Figure 9: Difference of growth rates for two-digits sectors. In Panel (b), the samples are divided into two groups: firms in the COVID-damaged sectors and in other sectors. The sample mean (median) is $-28.3\%(-23.6\%)$ and $-6.2\%(-1.0\%)$, respectively.

examines how this shock propagates via input-output linkages.

By using our firm-level data, we check this assumption and find which sectors are influenced the most by the pandemic. The left panel of **Figure 9** shows the sample average of sales growth rates for two-digits sectors. The worst-affected sectors are accommodation industry (75), road passenger transport business (43), food and beverage industry (76), and living-related, personal services industry (79).[9] It is reasonably interpreted that these the observed substantial negative growth rates for these sectors are due to the exogenous change in consumers' behavior to avoid crowded places. Although there are some ambiguity regarding this choice, we assume that these COVID-damaged industries are exogenously affected, playing the same role as exporting firms in Section 2.2. The right panel of **Figure 9** compares the distributions of growth rates for firms belonging to the COVID-damaged sectors with firm in other sectors. The growth rate for firms in the COVID-damaged sectors are lower by 22% on average. **Figure 10** compares the histograms of firms in the COVID-damaged sectors, firms in wholesale & retail sectors (our main sample), and firms having at least one customer belonging to the COVID-damaged sectors. In contrast to the case in Section 2.2, the most of firms in COVID-damaged sectors are small firms, which are connected even to small suppliers. This fact can be seen in the heatmap of the number of linkages given in **Figure 11**, which shows that the combinations between small customers and small suppliers are common. In our main analysis, we test whether negative shocks hitting firms in the COVID-damaged sectors are transmitted to these suppliers.

We focus on firms in wholesale & retail industry as main samples and examines whether their sales growth rate depend on whether their customers belong to the COVID-damaged sectors. Their summary statistics are given in **Table 2**. Similar to Section 2.2, let us consider the correlation of growth rates of firms and (the average of) their customers. The left-panel of **Figure 12**, in which samples are restricted to

[9]Other COVID-damaged sectors are (42) and (49), but the number of firms are quite small. We include these sectors in our analysis but it is unlikely that the inclusion affect our main finding.

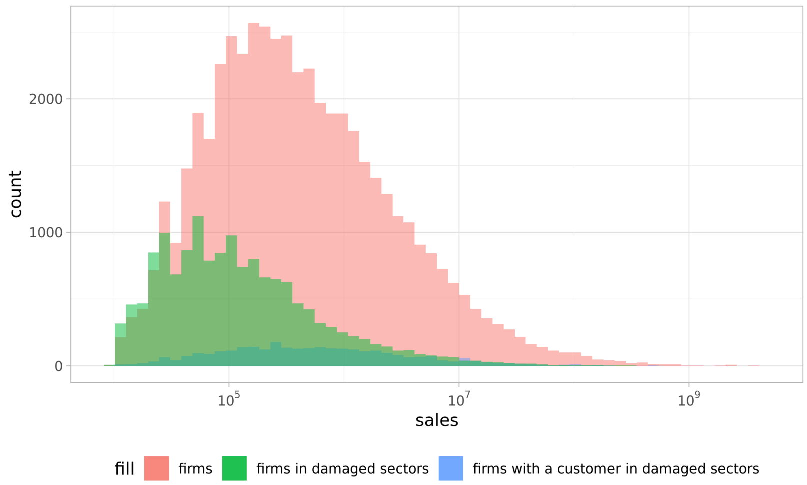


Figure 10: Histograms of firm sizes. Firms in wholesale & retail (red), firms in wholesale & retail (red) having at least one customer belonging to COVID-damaged sectors, and firms in COVID-damaged sectors are considered.

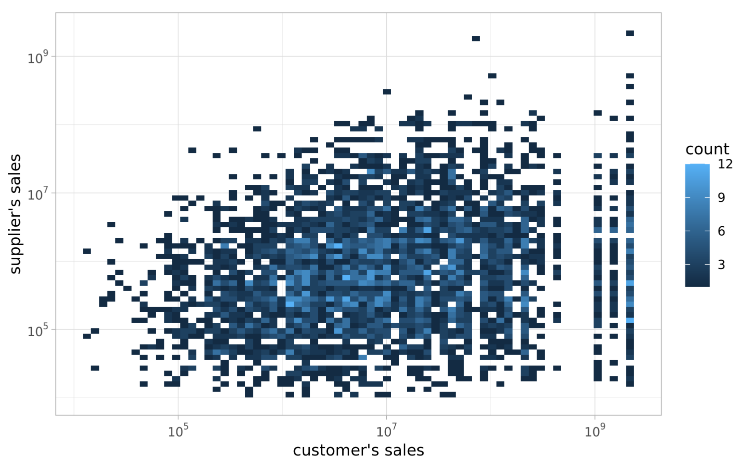
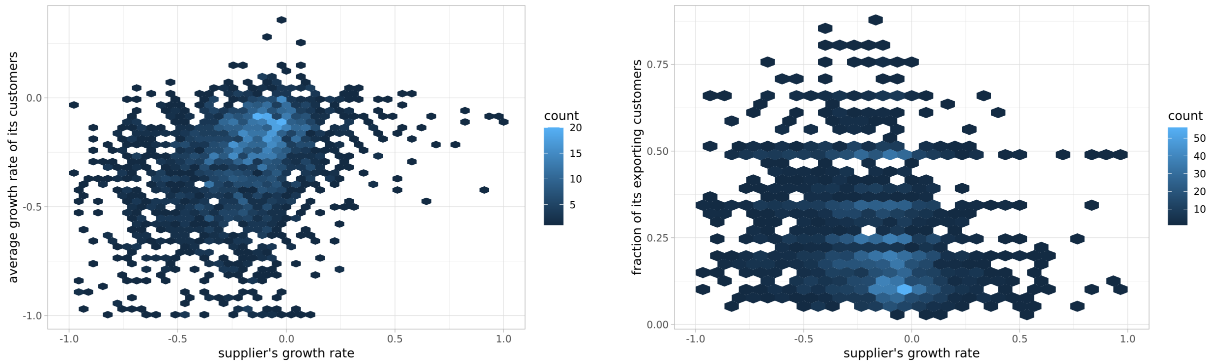


Figure 11: Heatmap of the number of links according to the firm sizes of suppliers and customers. We restrict samples for suppliers which belong to wholesale & retail sector and customers which belong to the COVID-damaged sectors.



(a) with customers' growth rates **(b)** with the fraction of customers in the COVID-damaged sectors

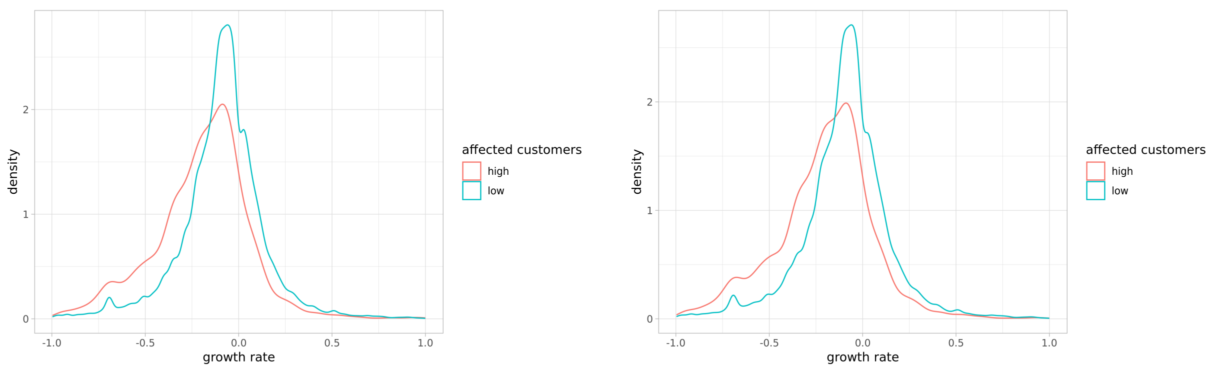
Figure 12: Dependence of sales growth rate. In Panel (a), samples are restricted to firms with 10% or more customers belonging to the COVID-damaged sectors. The correlation efficient is 0.327, which is larger than 0.213 without any restriction to samples.

suppliers with the fraction of customers belonging to the COVID-damaged sectors larger than 0.1, shows the positive correlation with the coefficient equal to 0.291. The right-panel depicts the heatmap of the growth rate of suppliers and the fraction of its customers belonging to the COVID-damaged sectors. Although the correlation coefficient is not so high compared with the case of the global financial crisis, it shows negative correlation of -0.109. These facts are consistent with the idea that negative shocks to firms in the COVID-damaged sectors are transmitted to their suppliers via input-output linkages.

name	count	mean	sd	q1	median	q3
growth rate of supplier	50559	-0.0796	0.2121	-0.1744	-0.0513	0.0000
log of supplier's sales	50559	12.9530	1.8668	11.5425	12.7075	14.1093
fraction of affected customers	50559	0.0210	0.1065	0.0000	0.0000	0.0000
average growth rate of its customers	50559	-0.0817	0.1518	-0.1393	-0.0639	0.0000

Table 2: Summary statistics of firms in wholesale & retail industry.

Note that the dependence discussed above does hold for small suppliers, in contrast to the case in Section 2.2. To check this point, dividing samples by the fraction of customers belonging to the COVID-damaged sectors, we compare the difference of the distributions of growth rates depends on the firm size of suppliers. The result is given in **Figure 13**, in which the criteria is chose to be 5 billion yen as in Section 2.2. This shows that when firms have many firms belonging to the COVID-damaged sectors, their growth rates become lower by about 9% on average. In addition, these two figures show that the difference of the distribution of growth rates does not depend on the firm size of suppliers. That is, even small suppliers are subject to shocks transmitted from their customers. These figures suggest that the fraction of firms in the COVID-damaged sectors seems to be an important variable to explain the variation of growth rate of suppliers, and thus, can be used as an instrumental variable. In the next section, we develop an estimation model to measure the



(a) Full samples

(b) Small suppliers

Figure 13: Density estimation of growth rates for firms in manufacturing and wholesale & retail industries. In each panel, samples are divided by the fraction of firms belonging to the COVID-damaged sectors (i.e., larger than 0.1 or not). In Panel (a), the mean (median) of growth rates is $-0.169(-0.122)$ for the firms with 10% or more customers in the COVID-damaged sectors. The mean (median) of growth rates is $-0.0745(-0.0408)$ for the other group.

propagation effect using this variable as an instrument.

3 Empirical Model

This section provides our empirical model, which entails the heterogeneity of the propagation effect, and explains our identification strategy.

3.1 Estimation equation

To measure the propagation effect of demand shocks, we use the heterogeneous treatment effect model developed by Athey et al. (2019). Let $Y_i \in \mathbb{R}$ be the sales growth rate of firm i (supplier), that is, the main outcome variable in our analysis, and let X_i be firm i's covariates. We use the average growth rates of i's customers, denoted by W_i, as a treatment variable. The main estimation equation is given by

$$Y_i = \mu(X_i) + \tau(X_i)W_i + \varepsilon_i$$

where $\tau(X_i)$ represents the causal effect of W_i on Y_i, that is, the propagation effect of demand shocks.[10] We do not assume that $\mu(X_i)$ is a linear function of X_i but estimate $\mu(X_i)$ by a machine-learning method.[11] Furthermore, we assume that the propagation effect $\tau(X_i)$ may depend on firm i's covariates, that is, the propagation effect is heterogeneous across firms. Here, ε_i represents a noise term, which may be correlated with W_i.

[10] Since the weight of transaction, such as transaction volume, is not available in our data, we take as W_i the simple (unweighted) average of the sales growth rates of the customers which are reported as i's main customers by firm i.

[11] We take the two-digit industry classification and the logarithm of firm size as arguments for $\mu(X_i)$.

When ε_i is correlated with W_i, the estimation would be biased. To isolate the propagation effect from this bias, we need an instrument variable, denoted by Z_i, which is independent of ε_i conditional on X_i. As an instrumental variable, we choose the fraction of exporting firms among firm i's customers.[12] Then, we can identify the heterogeneous effect $\tau(x)$ as follows:

$$\tau(x) = \frac{\text{Cov}[Y_i, Z_i \mid X_i = x]}{\text{Cov}[W_i, Z_i \mid X_i = x]}$$

The propagation effect can be seen as the local averaging treatment effect at $X_i = x$. In practice, we use the moment conditions to get $\hat{\tau}(x)$:[13]

$$\mathbb{E}[Z_i(Y_i - W_i\tau(x) - \mu(x)) \mid X_i = x] = 0$$

$$\mathbb{E}[Y_i - W_i\tau(x) - \mu(x) \mid X_i = x] = 0$$

The choice of the arguments in $\tau(X_i)$ depends on research questions. In our analysis, we focus on the size dependence of the propagation effect, that is, the size of a supplier and the (average) size of its customers. As seen in Section 2.2, the propagation effect appears to be more profound for large firms, and by using the heterogeneous treatment effect model,m, we can quantify the degree of the heterogeneity of the propagation effect. Furthermore, the size dependence is crucial for the literature on the micro-origins of aggregate fluctuations. As mentioned in Section 1, in this literature, large firms having transactions with many suppliers and customers play a key role in spreading microeconomic shocks across an economy, resulting in micro-originated aggregate fluctuations. By focusing on the size dependence of the propagation effect, we can test the empirical relevance of this idea in terms of the demand-shock propagation. In addition, it is known that there are many transactions between large customers has small suppliers, which accounts for the majority of the links in an observed network. This empirical fact is one of the reason why microeconomic shocks hitting the large firms are considered to easily propagate across an economy. By considering both sizes as arguments of $\tau(X_i)$, we can assess the importance of these links in the demand-shock propagation.

3.2 Identification strategy

Since our identification of the propagation effect relies on the IV method, it is necessary to check the validity of an instrumental variable. For the case of the global financial crisis, we use the fraction of exporting firms among i's customers as the instrumental variable. Similarly, for the case of pandemic, we use the fraction of firms belonging to the COVID-affected sectors as the instrumental variable. To confirm that these variables are an appropriate instrumental variable, we provide supportive evidences for the two requirements: causality and exclusion conditions.

Consider the case of the global financial crisis. First, we check the causality condition, that is, the status of being an exporting firm leads to the decline in the growth rate of the firm. Indeed, this is justified by the

[12]For the validity of the instrumental variable, see Section 3.2.

[13]In implementation, we use R package grf developed by J. Tibshirani, S. Athey, E. Sverdrup, and S. Wager. See `https://grf-labs.github.io/grf/`

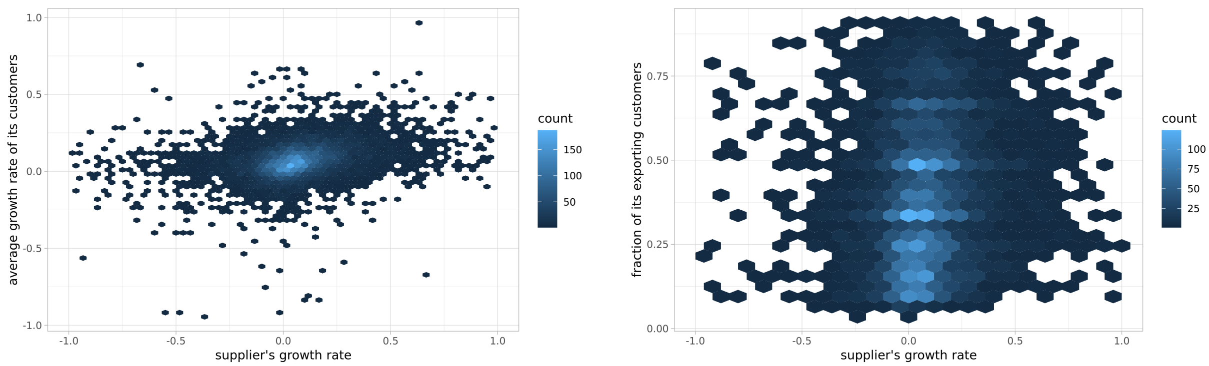
exogeneity of the event and subsequent decline in exports in Japan; the global financial crisis triggered the sharp drop in exports and then damaged the exporting firms as seen in **Figure 5**. The causality goes from the status of being exporting firm to its growth rates, not vice versa. Thus, the higher the fraction of exporting firms among its customers, the lower the (average) growth rates of its customers, which satisfies the required causality condition.

For exclusion condition, the path connecting the fraction of exporting customers and the growth rate of the supplier must be unique. We need to check that there is no other path through which the two variables are interrelated. Imagine the case where the status of being exporting or not depends on its own condition but not on its suppliers' conditions. For example, in Melitz (2003), the status of being exporting is determined by the firm's productivity but not by its suppliers' one. In such a case, even when firm's productivity is related to its growth rate, there is no direct link between the status of being exporting and its suppliers' growth rates, and thus, the exclusion condition would be satisfied.

The remaining concern is the case where there exists some hidden factor leading to sales growth and directly related to the choice of being exporting or not for its customers. For example, imagine that high productivity of a supplier leads to its sales growth and lowers the marginal costs of its customers, which induces the customers to export. This type of a model has been discussed in the literature (see, e.g., Section 3 in Bernard and Moxnes (2018)). However, under this assumption, the relationship between the sales growth rates and the fraction of exporting firms among its customers would be positive, which contradicts the negative correlation as seen in **Figure 6**.

More generally, consider the case that there exists some factor leading to negative sales growth and inducing the firm to choose exporting firms as its customers. If such factor determines the relation between the fraction of exporting customers and growth rate of the suppliers, the negative correlation would be observed not only in the periods of the global financial crisis but in the normal periods prior to the global financial crisis. To test this point, we consider firms' growth rates in 2006-2008, during which exports from Japan has been increasing as shown in **Figure 2**. **Figure 14**, which correspond to **Figure 6**, provides the dependence of sales growth rates of suppliers on those of its customers (left panel) and on the fraction of exporting customers (right panel). While the positive correlation is observed in the left panel as in **Figure 6**, the right panel shows that the growth rate of suppliers are positively correlated with the fraction of exporting customers. This indicates that the negative correlation observed during the financial global crisis is not driven by some hidden factors, but it is reasonable to consider that it is driven by an increase/decrease in exports, as required by the exclusion condition. Therefore, these justifications make us confident that the fraction of exporting customers is an appropriate instrument variable.

Similar justification can be applied to the case of the COVID-19 pandemic. Since the pandemic is an exogenous event for firms, the causality runs from the status of being in the COVID-damaged sectors to its growth rates, not vice versa. In addition, since this negative impact is strong enough as seen in **Figure 9**, the



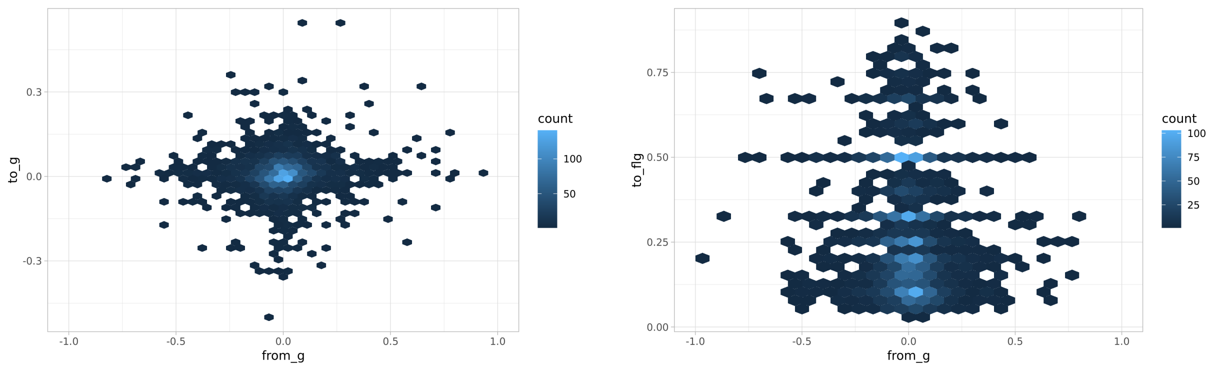
(a) with customers' growth rates **(b)** with the fraction of exporting firms among its customers

Figure 14: Dependence of sales growth rate during the period prior to the global financial crisis. For other points, see the explanation in **Figure 6**.

required causality condition is satisfied. For exclusion condition, we consider that the status of belonging to the COVID-damaged sectors has an effect on the growth rates of their suppliers during the period prior to the COVID-19 pandemic. **Figure 15** shows the dependence of sales growth rates on the (average) growth rates of its customers and fraction of its customers belonging to the same COVID-damaged sectors in 2018-2019, which corresponds to **Figure 12**. The right panel shows that the correlation between the growth rate and fraction of its customers in the COVID-damaged sectors is much weaker, though the correlation coefficient is still negative (-0.017). In addition, the left panel shows that the positive correlation of the growth rates between suppliers and customers is obscure in this period, suggesting that without the COVID-19 pandemic, neither the growth rate of customers nor the fraction of its customers in the COVID-damaged sectors affect these suppliers substantially. Thus, it is reasonable to assume that an exogenous change in consumers' behavior damages the firms in the sectors, and then negative shocks affect their suppliers, leading to the strong positive correlation between these variables, which are not observed prior to the COVID-19 pandemic. From these empirical facts, we confirm that the fraction of its customers in the COVID-damaged sectors satisfies the requirements of the instrumental variables.

4 Empirical Results

This section provides our main findings of the propagation effect. Section 4.1 provides the results for the case of the global financial crisis. Section 4.2 provides the results for the case of the COVID-19 pandemic.



(a) with customers' growth rates

(b) with the fraction of customers in the COVID-damaged sectors

Figure 15: Dependence of sales growth rate during the period prior to the COVID-19 pandemic. For other points, see the explanation in **Figure 12**.

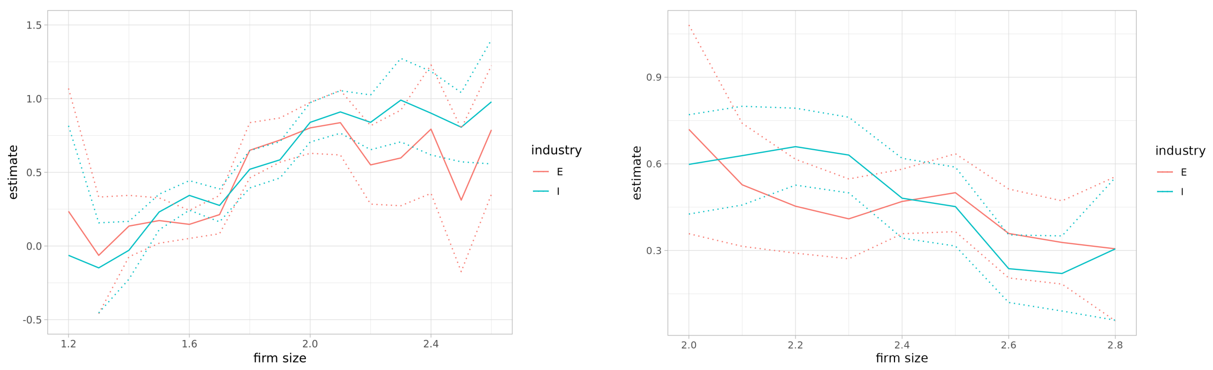
4.1 Global financial crisis

4.1.1 Heterogeneous effect

Based on the method in Section 3, we estimate the propagation effect of demand shocks $\tau(X)$ in the case of the global financial crisis. First, we consider the (log) size of a supplier as the unique argument of $\tau(X)$. The result is given in the left-panel of **Figure 16**, showing that the estimate of $\tau(X)$ is an increasing function of the size of the supplier and becomes flat above 5 billion yen. In particular, the estimate of $\tau(X)$ for small suppliers is close to 0, and indeed, not significantly different from 0. That is, the propagation effect is more profound for large suppliers, while the growth rates of small suppliers do not respond to the negative growth rates of their customers driven by the drops in exports. This result is consistent with our pre-analysis in Section 2.2; that is, during the global financial crisis, negative demand shocks are transmitted only to large suppliers.

Next, we consider the (log of) geometric mean of the sales of the firm's customers as the unique argument of $\tau(X)$. The result is given in the right-panel of **Figure 16**. In contrast to the case of the supplier's size, the estimate of $\tau(X)$ is decreasing in the average size of its customers, especially for wholesale $\&$ retail Industry. That is, when exporting firms hit by the sharp drops in exports are large, its negative shock coming from this large exporting customer appears to be weak for its suppliers.

We add the both sizes of suppliers and customers into the arguments of $\tau(X)$ to see how the combination of the two firm sizes is related to the heterogeneity of the propagation effect. **Figure 17** shows the result of the dependence of $\tau(X)$ on the two firm sizes for manufacturing and wholesale $\&$ retail industries. Both figures show that, as suggested by **Figure 16**, the estimate of $\tau(X)$ is close to 0 when suppliers are small and their customers are large. That is, demand shocks does not propagate through the links between small suppliers and large customers. Since during the global financial crisis, firms influenced by negative shocks are large exporting firms (large customers), our result means that the effect of the drop in exports do not



(a) Size of a supplier

(b) Size of its customers

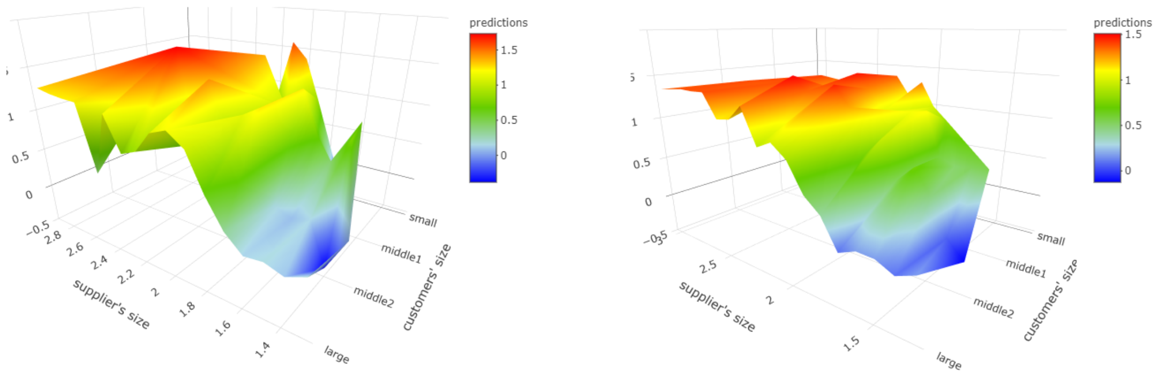
Figure 16: Estimate of the propagation effect $\tau(X)$. In panel (a), the unique argument of $\tau(X_i)$ is the size of a supplier. The unit is the log of the supplier's sales (with base equal to 2000). In panel (b), the unique argument of $\tau(X_i)$ is the geometric average of its customers' sizes. The solid line is the point estimate of the propagation effect $\tau(X)$. The dotted lines are the upper and lower bound of its confidence interval, respectively. Industry E (I) represents manufacturing (wholesale & retail).

propagate across Japanese economy as a whole but is concentrated to large firms and their large suppliers only.

To summarize, our analysis shows two findings: the statistically and economically significant propagation effect of demand shocks and its heterogeneity. As emphasized in the literature, our analysis confirms that demand shocks driven by sharp drops in exports propagate through an input-output network and affect non-exporting firms. However, in contrast to the naive presumption used in the literature (e.g., Herskovic et al. (2020)), the propagation effect is not homogeneous across firms but depends on the sizes of supplier and customers. In particular, the propagation does not occur between small suppliers and large customers. An obvious question is how this could be the case. In the following, we examine the reason for this heterogeneity.

4.1.2 Mechanism

We begin with the behavior of exporting firms during this period. The first clue is given by the time series of aggregate data in **Figure 2**, showing that not only the drop in exports but the decline in inventories are important factor for the recession of Japanese economy. In particular, we observe an increase in inventories in 2008Q4, which is consistent with the unexpected demand shocks and the sharp decline afterwards. That is, after realizing the start of the recession in foreign countries, firms rush for the adjustment of the level of inventories. This can be confirmed in our samples as well. **Figure 18** shows the density estimation of the growth rate of inventories for each year. Only during this period (2008-2010), the distribution of the growth rates shifts to the left, and after this period, it returns to the original location. Furthermore, **Figure 19** shows that the scatter plot of the sales growth rates and inventory growth rates. The positive correlation suggests that the inventory adjustment is dominant in their behavior. Put differently, facing the negative demand

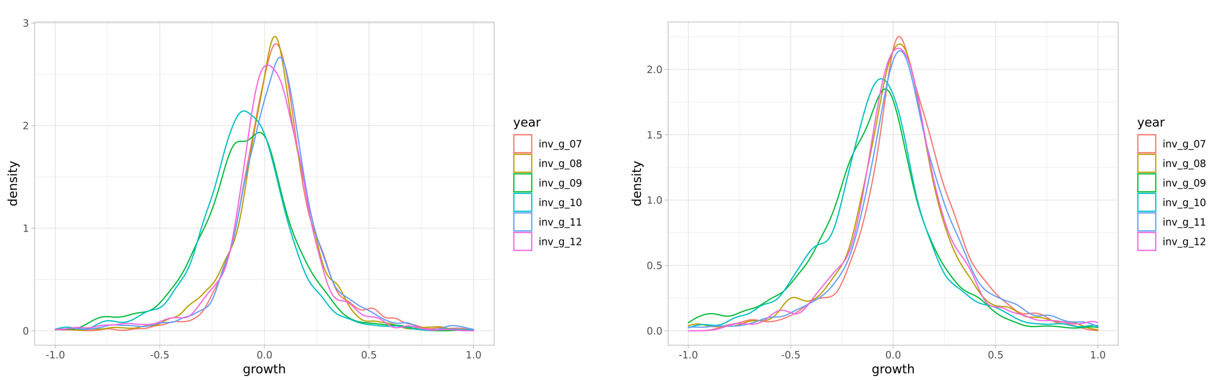


(a) Manufacturing **(b)** Wholesale & retail

Figure 17: Estimate of $\tau(X)$. The arguments of $\tau(X)$ are the log sizes of suppliers and their customers. For the size of its customers, it is categorized into four groups: small (sales $\leq$ first quantile), middle1 (first quantile $\leq$ sales $\leq$ median), middle1 (first quantile $\leq$ sales $\leq$ median), middle2 (median $\leq$ sales $\leq$ third quantile) and large (sales $\geq$ third quantile).

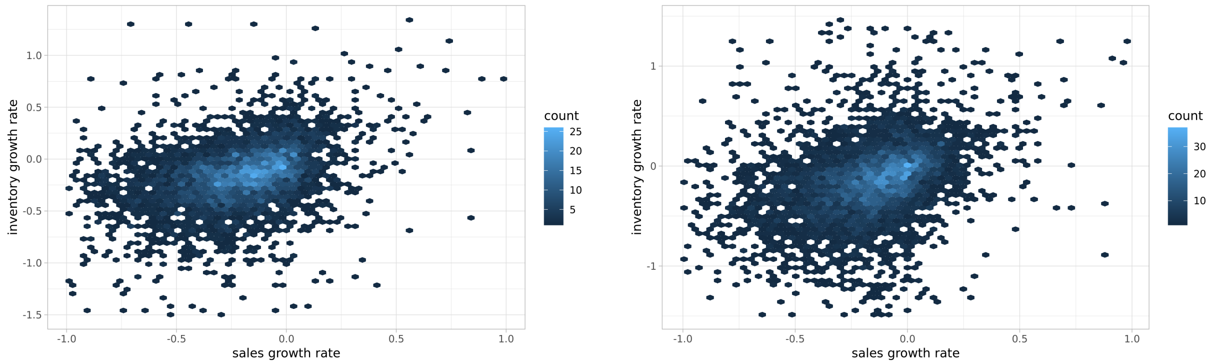
shocks caused by the global financial crisis, exporting firms reduce their production even more not only to compensate the decrease in exports but to adjust to the new level of inventories. Thus, the weak propagation from large customers found in **Figure 16** does not mean that large exporting firms continue to buy from their suppliers and act as a buffer against the shock.

Why were small firms not influenced by the negative shocks to their customers, even when their customers reduce the production and inventories? Another possible explanation for the heterogeneity of the propagation effect is an extensive margin; that is, facing the decline in the production of their existing customers, small firms may compensate the decline in demand by finding other customers. However, as seen below, our data suggest that this explanation is highly unlikely. First, **Figure 20** shows the relation between



(a) Manufacturing **(b)** Wholesale, retail

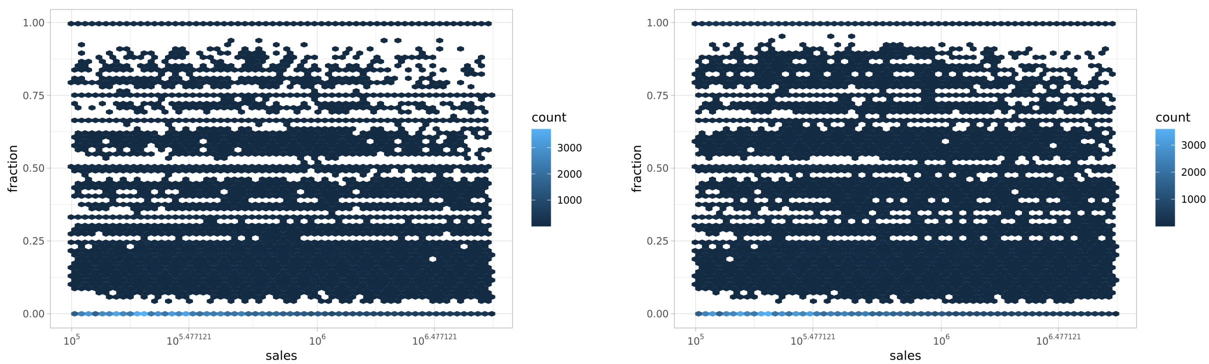
Figure 18: The density estimate of the growth rate of inventory for exporting firms. We restrict our samples to firms with size larger than 5 billion yen.



(a) Manufacturing

(b) Wholesale, retail

Figure 19: Scatter plot of the sales growth rates and inventory growth rates for exporting firms. We restrict our samples to firms with size larger than 5 billion yen.



(a) Fraction of links lost

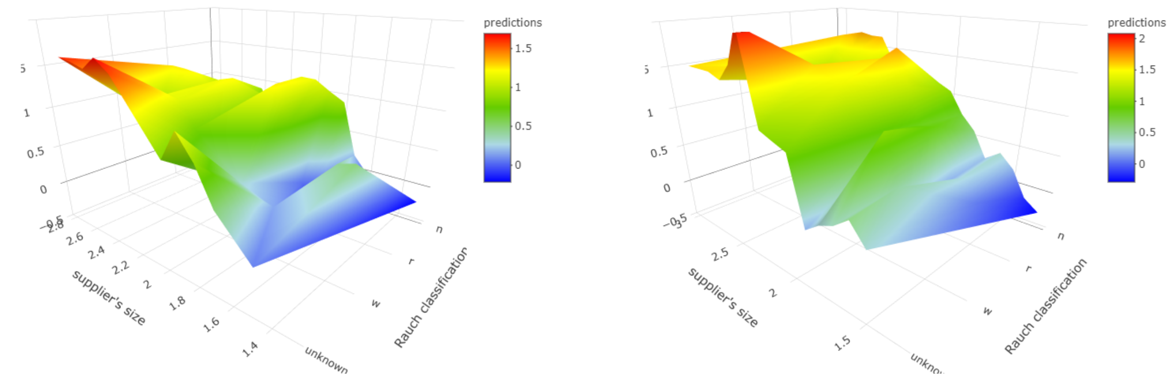
(b) Fraction of links newly created

Figure 20: Scatter plot of firm size and the fraction of links lost and newly created during the global financial crisis.

firm size and the fraction of links lost and newly created during the global financial crisis. This figure shows that there is no clear relation between them, and in particular, that most of small firms do not change their customers. Since the decline in inventories for exporting firms is widely observed, the extensive margin cannot explain the heterogeneity of the propagation effect.

Furthermore, we test whether the heterogeneity of the propagation effect depends on how differentiated the products are by using Rauch classification of sectors (see Rauch (1999)).[14] This classification categorizes goods (or sectors) into three categories: differentiated goods (denoted by n), goods with a referenced price (r), and commodity goods (w). **Figure 21** shows the estimate of $\tau(X_i)$, where the size of a supplier and Rauch classification are the arguments of $\tau(X_i)$. This figure suggests that the size dependence of $\tau(X_i)$

[14]This classification is also used in Barrot and Sauvagnat (2016), in which they find that the specificity of inputs are important for the downstream propagation of supply shocks. That is, when firms producing differentiated goods, which are difficult to substitute, are disrupted by natural disasters, its propagation effect for their customers is more enhanced compared to firms producing commodity goods. In contrast to this finding about the supply-shock propagation, our results suggest that the input specificity has only a minor role in the demand-shock propagation.



(a) Manufacturing

(b) Wholesale, retail

Figure 21: Estimate of $\tau(X_i)$ As the arguments of $\tau(X_i)$, the size of a supplier and Rauch classification are used.

is still observed and that the estimate of $\tau(X_i)$ does not depend on the Rauch classification. That is, the heterogeneity of $\tau(X_i)$ is not related to the extensive margin of network links.

To summarize, the above empirical examinations suggest that small suppliers remain intact and do not change transaction relation with their customers, while their large customers actually reduce the production and inventories. Why are these large customers able to reduce their production and inventories without changing the amount of purchase from the small suppliers? A possible explanation is that the supply from these small suppliers accounts for only a minor part of inputs of their large customers, that is, the transaction between these firms are not viewed as important from the customers' sides. To check this point, we focus on reports from customers' side, that is, reports about the main suppliers of the customers. We consider whether the link reported by suppliers are also reported by the corresponding customers. Recall that firms are asked to report only major transacted firms, and thus, links reported by both sides means that the suppliers are viewed as the major transacted suppliers from the customers's viewpoints, and vice versa. **Figure 22** shows the fraction of the links reported by both sides according to the two firm sizes. This clearly shows the size dependence; that is, larger firms are likely chosen as main suppliers among many suppliers. Because of this asymmetry, even when small suppliers views their customers as main ones, the suppliers are not viewed as main ones from customers' viewpoint. This asymmetry link is common in our data. Indeed, as seen in **Figure 4**, there are many links between small suppliers and large customers, but most of these links are viewed as important from suppliers but not from customers. This asymmetry coincides with the heterogeneity of the propagation effect shown in Section 4.1.1; if demand shocks propagate only to main suppliers of the firms facing negative shocks, the propagation effect would be small for small suppliers having large customers.

Finally, to confirm that shocks through links reported by both sides are more transmissible, we divide the samples into two groups according to the fraction of these links. The left (right) panel of **Figure 23**

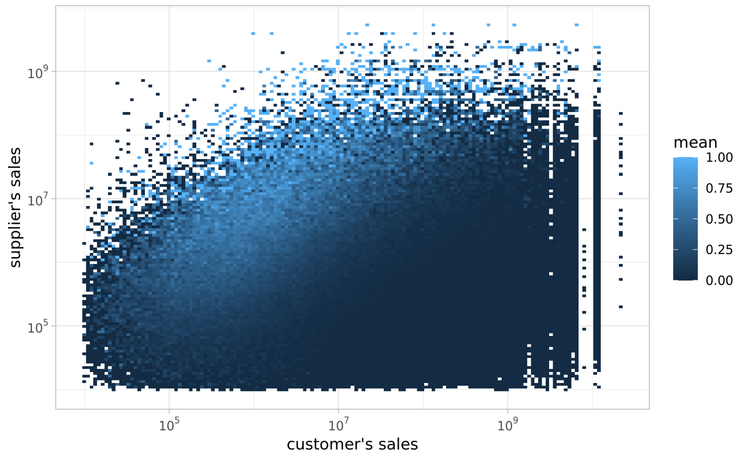
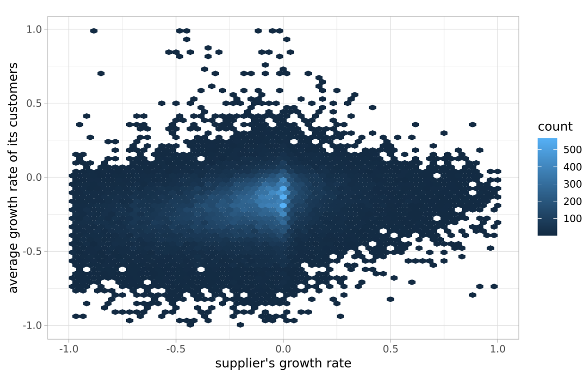
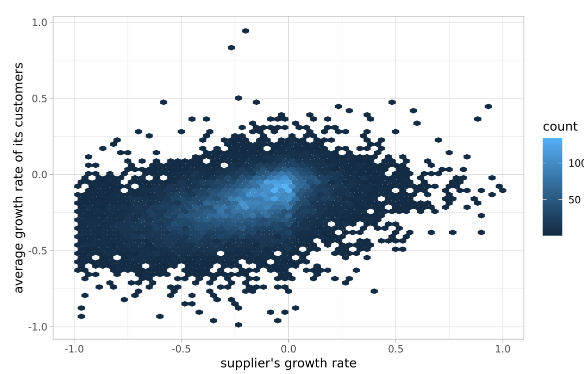


Figure 22: Asymmetry of links according to firm size. If the link reported by suppliers are also reported by the corresponding customer, we set the value to 1. We take the average of this value for each cell.



(a) Firms with fraction less than 0.1



(b) Firms with fraction larger than 0.1

Figure 23: Scatter plot of the sales growth rates. Samples are restricted to firms with sales less than 5 billion yen.

depicts the scatter plot of growth rates for suppliers having the fraction more (less) than 0.1. In particular, we restrict the samples to firms with sales less than 5 billion yen, that is, the group of firms which has weak propagation effect. Even for this group, this figure shows the higher correlation for suppliers having the higher fraction of links reported by both sides. Indeed, the correlation coefficient increases from 0.276 (left panel) to 0.421 (right panel). These results suggest that the transmissibility of shocks depends on the types of links, and that only when the links are important for both suppliers and customers, the demand shocks propagate to the suppliers.

Although we do not fully rationalize these firms' behavior facing negative demand shocks, it is worth mentioning several possibilities consistent with our finding. The first one is that the inputs supplied by small suppliers are fixed inputs, and therefore, the sales of the suppliers are independent of the inventory adjustment of large exporters (customers). However, to the best of our knowledge, there is no empirical evidence showing that small firms supply fixed inputs to large customers. A more likely explanation is that the inputs supplied by small suppliers are not directly connected to the main business of its large customers. That is, the amount of inputs supplied by these small suppliers are not determined by that of outputs produced by its customers, and therefore, its sales growth rate does not respond to the inventory adjustment of its customers. This explanation is consistent with the fact that most of small suppliers with large customers are not viewed as main suppliers by the corresponding large customers. Finally, it should be noted that due to the limitation of our data, we cannot distinguish changes in price and quantities in our analysis. Regarding this point, the finding by Heise (2019) gives us another insight: he finds that the prices of suppliers' products are more responsive when the two firms have a long-term relationship. If the relationships reported by both firms as main transaction in our data correspond to these long-term relationships, the price of suppliers responds more strongly to the negative demand shocks hitting their customers, and therefore, the propagation effect via these relationships would be more profound.

To summarize, our analysis for the case of the global financial crisis shows that demand shocks do not propagate equally to their suppliers but only to the main suppliers, which are typically large firms (see **Figure 1**). In addition, since the exporting firms are large, this means that the propagation occurs mainly between large firms. This is one of the main features of the demand-shock propagation during this period. One might think that if small firms (customers) face negative shocks and their suppliers are also small, the shock propagation can occur between these small firms. As shown in Section 4.2, this is what happened during the COVID-19 pandemic.

4.2 COVID-19

Given the implications in Section 4.1, we apply the same analysis to the case of the COVID-19 pandemic but in reverse order: we first analyze the link dependence on firm size and then provide the estimate of the propagation effect of demand shocks. The analysis in the following provides another support for the

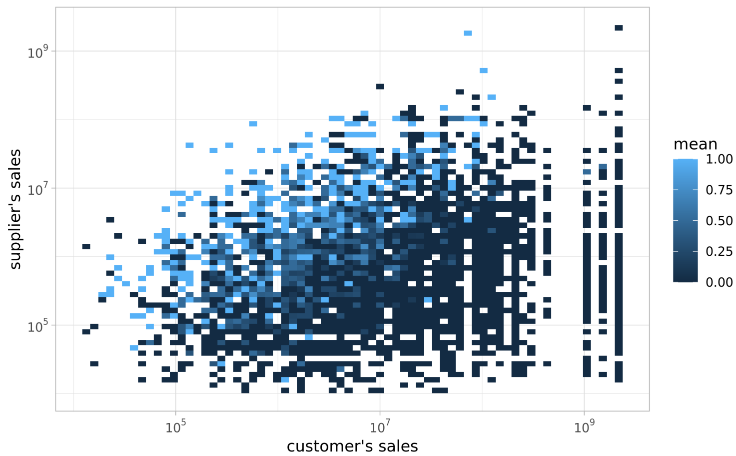
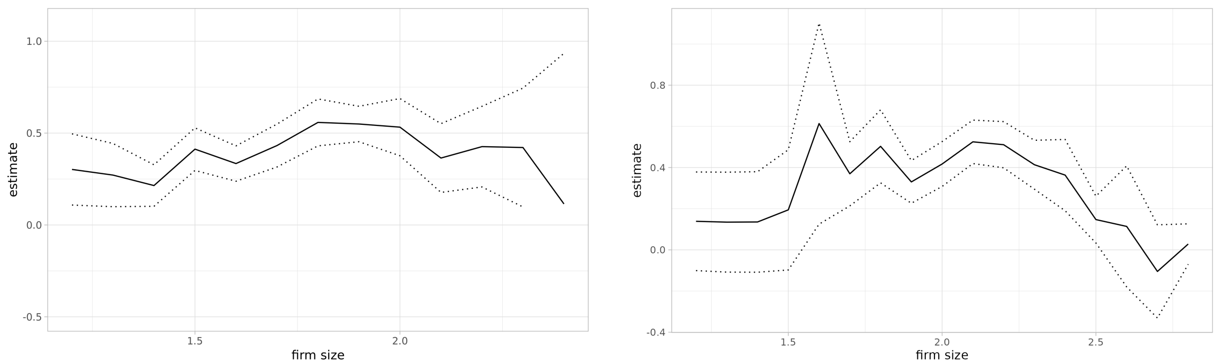


Figure 24: The likelihood that the links reported by suppliers are also reported by the corresponding customers. The fraction of the links reported by both sides are calculated for each cell.

interpretation that demand shocks propagate to their suppliers only when the suppliers are the major ones for the customers.

First, let us consider links between firms (customers) in the COVID-damaged sectors and their suppliers. **Figure 24** shows the fraction of links reported by both sides, that is, the likelihood that the link reported by suppliers as main is also reported by the same customers as main. In contrast to **Figure 22**, even for small suppliers, the significant fraction of links reported by suppliers are also viewed as main by their customers. This suggests that in contrast to the case of the global financial crisis, in which propagation occurs mainly between large firms, demand shocks propagate to small firms as well. The absence of the heterogeneity of the propagation effect would be another evidence that demand shock propagation occurs only when the suppliers are important suppliers for the corresponding customers.

To test this idea, we estimate the propagation effect using the method in Section 3. First, we consider the size of the supplier as the unique argument of $\tau(X)$. The estimation result is given in the left-panel of **Figure 25**. This figure shows that the estimate of $\tau(X)$ has no strong heterogeneity and is economically and statistically significant even for small suppliers. Negative shocks hitting firms in the COVID-damaged sectors are transmitted to their small suppliers via transaction linkages. This result is in contrast to the case of the global financial crisis, where the propagation effect is not statistically significant for small suppliers. This difference can be interpreted that in the case of the pandemic, firms experiencing negative shocks are small, and moreover, their main suppliers are also small as seen in **Figure 24**. Furthermore, the right-panel of **Figure 25** shows the estimate of $\tau(X)$ when the average size of customers are considered as the argument of $\tau(X)$, and **Figure 26** considers the both sizes as the arguments of $\tau(X)$. These figures show that the propagation of negative shocks from large customers is weaker, but the heterogeneity is not profound compared to the case of the global financial crisis. In other words, the feature of the propagation during this



(a) Size of suppliers

(b) Size of customers

Figure 25: Estimate of the propagation effect $\tau(X)$. In panel (a), the size of a supplier is the unique argument of $\tau(X_i)$. In panel (b), the geometric mean of the size of its customers is the unique argument of $\tau(X_i)$. The dotted lines represent the upper and lower bound of confidence interval at the 5% level.

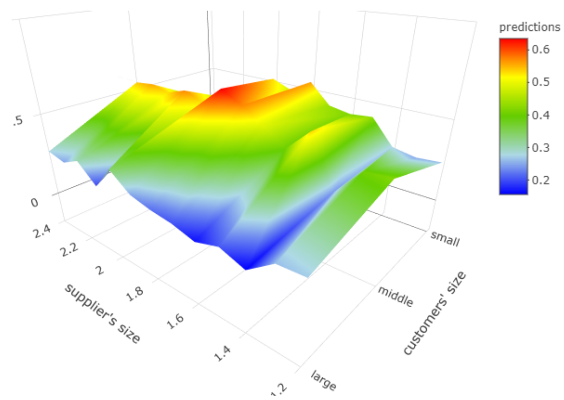


Figure 26: Estimate of the propagation effect $\tau(X)$. The arguments of $\tau(X)$ are the log sizes of suppliers and their customers.

period is that shocks spread widely including small firms.

To summarize, our analysis shows that the propagation effect of demand shocks has heterogeneity and depends on the firm sizes of suppliers and customers. This reflects that the importance of the links are related to the size of the suppliers, that is, large suppliers tend to be chosen as major suppliers for customers. This is why the propagation effect is more profound for large suppliers during the global financial crisis. However, since the major suppliers of the firms facing negative shocks during the COVID-19 pandemic are small, the negative shocks propagate to their small suppliers as well. We conclude that firm sizes and link type are key in the demand-shock propagation.

5 Conclusion

The propagation of shocks has been one of the oldest themes in macroeconomics, which at least dated back to Leontief's works, and renewed interest in the last decade have represented the great importance of this theme even today. In particular, the increasing accessibility of firm-level data enables us to identify the network structure and to directly observe how shocks propagate on the network, shedding new insights to this literature. However, there is still room for further investigation on this theme: in previous studies, the demand-shock propagation via firm-level input-output linkages has not fully analyzed, and furthermore, the heterogeneity of the propagation effect has been ignored. Our paper tackles this problem by exploiting two events (the global financial crisis and COVID-19 pandemic) in Japan and aims to get a further implication about the shock propagation on a network.

We find that the propagation effect is statistically and economically significant. As expected, in terms of sales growth rates, firms are negatively affected when their customers are exporting firms during the global financial crisis. Furthermore, our analysis reveals that this propagation effect shows the heterogeneity, that is, it depends on both firm sizes (i.e., supplier and customer). Negative shocks originating from the sharp drop in exports are transmitted mainly to large suppliers, and other small suppliers remain unaffected. In contrast, during the COVID-19 pandemic, we find that the heterogeneity of the propagation effect is weak, that is, negative shocks are transmitted to small firms as well. This difference is due to that demand shocks propagate to a supplier only when the supplier, which reports its customers as main ones, is also reported as a main supplier from the customers. During the global financial crisis, most of exporting firms and their main suppliers are large firms, and therefore, demand shocks are transmitted only to these large suppliers. For this reason, small supplier having transactions with large customers, whose combination accounts for the majority of links in the observed network, remain unaffected. During the COVID-19 pandemic, most of firms belonging to the COVID-affected sectors and their main suppliers are small, and therefore, negative shocks are transmitted to these small suppliers as well.

Our finding indicates that the number of suppliers, which is typically large for large customers, does not necessarily represent the importance of firms in term of demand-shock propagation. In fact, especially during the global financial crisis, negative shocks are transmitted to large suppliers only, that is, the many links between small suppliers and large customers (i.e., exporting firms) are not relevant for the demand-shock propagation. In light of our finding, we conclude that the role of large firms in shock propagation has been overemphasized in the literature. We believe that our new finding contributes to the literature by revealing the importance of the heterogeneity of the propagation effect.

Finally, it is worth mentioning the limitations of our analysis. Although our analysis aims to identify the causal effect of demand shocks, it says nothing about the mechanism generating the heterogeneity of the propagation effect. For example, due to lack of this point, it is not obvious that our finding can be generalized to the case where positive demand shocks, rather than negative demand shocks, are the initial shocks for the propagation. To answer such question, it is necessary to generalize a theoretical model and to fully characterize firms' behavior in the face of demand shocks. In the recent literature, beyond the classical model by Acemoglu et al. (2012), many generalizations have been proposed so far (e.g., the introduction of extensive margin by Grassi (2017) and inefficiencies generating positive markup by Bigio and La'o (2020) and Baqaee and Farhi (2020b)). We believe that our finding about the heterogeneity of the propagation effect can be viewed as another possible generalization of existing models for better understanding of propagation phenomena.

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