ERIA-DP-2023-10

ERIA Discussion Paper Series

No. 482

The COVID-19 Pandemic and World Machinery Trade Network†

Kozo KIYOTA‡

Keio University, Research Institute of Economy, Trade and Industry (RIETI), and Tokyo Center for Economic Research (TCER)

August 2023

Abstract: In light of the importance of the machinery trade in global trade, this study examines whether the patterns of machinery exports changed significantly after the COVID-19 pandemic. Frameworks of network analysis and structural break analysis are applied to monthly level bilateral export data from January 2016 to March 2022. The main findings are threefold. First, positive structural change is found in exports in major machinery-exporting countries. Second, negative structural change in centrality is found in Japan and some ASEAN Member States (AMS), which implies a decline in the relative importance of these countries in the global machinery network. Third, the decline in Japanese centrality was not caused by the decline in export values or number of destination countries. Rather, it is attributable to the decline in the centrality of Japan's export destination countries such as AMS. Noting that Japan has a relatively strong trade relationship with AMS, these results together suggest that the negative shock of the pandemic spread throughout the supply chain, which led to the decline in the relative importance of some countries – such as Japan – in the global machinery trade network.

Keywords: Machinery trade; COVID-19 pandemic; Network; Centrality
JEL classification: F14, F40

† The author has benefited from conversations on this topic with Fukunari Kimura as well as from comments on earlier drafts from Doan Ha, Paresh Kumar Narayan, Shujiro Urata, and Hongyon Zhang. This research was supported by the Economic Research Institute for ASEAN and East Asia (ERIA) project, Global Trade and Economic Recovery in the Post-Pandemic World. The author also acknowledges the financial support of the Japan Society for the Promotion of Science (JSPS) Grants-in-Aid (JP22H00063). The usual disclaimer applies.

‡ Keio Economic Observatory, Keio University, 2-15-45, Mita, Minato-ku, Tokyo 108-83345, Japan. E-mail: kiyota@keio.jp

1. Introduction

Whether and how the global supply chain is resilient to various shocks – such as the COVID-19 pandemic – is a concern for policymakers. Supply disruptions caused by shocks such as Brexit, the pandemic, and the Russian invasion of Ukraine have pushed the issue of risk in global supply chains to the top of many policy agendas (Freeman and Baldwin, 2022); for example, the United States (US) is concentrating on building resilient supply chains (White House, 2022).

Although 2020 was marked by some of the largest reductions in trade since World War II, the global economy is rapidly recovering. According to the International Monetary Fund (2022), global output growth was –3.1% in 2020, recovering to 5.9% in 2021. Similarly, world trade volume declined –8.2% in 2020 but increased 9.3% in 2021. These estimates suggest that the negative impacts were temporal rather than perpetual. In other words, trade was indeed resilient against the shock of the pandemic.[1]

When discussing supply chains, however, many refer to manufacturing products (e.g. iPads, cars, and aircraft) rather than trade as a whole, because they have many parts and components whose production processes are spread across different countries. While the negative effect of the pandemic on the overall goods trade did dissipate because of a V-shaped recovery, the effect on machinery trade remains inconclusive.[2]

Ando, Kimura, and Obashi (2021) examined the impacts of the pandemic on Japanese machinery trade. Using data between January 2017 and October 2020, their results indicated that trade relationships for parts and components were robust, even amidst the pandemic. Moreover, international production networks in machinery sectors stayed almost intact. Ando, Kimura, and Yamanouchi (2022) found that the negative impacts of the pandemic on exports were much smaller for East Asia than for North America and Europe.

In contrast, Arriola, Kowalski, and van Tongeren (2021) argued that the variation in trade impacts across different product categories in 2020 was larger than during the 2008–2009 global financial crisis – and greater than in any other year over the past 2 decades. Based on detailed descriptive analysis of trade data between January 2000 and January 2021, they

---

[1] In this paper, the focus is limited to the goods trade due to the limited availability of monthly data. Ando and Hayakawa (2022) utilised quarterly data and examined the impact of the pandemic on trade in services, discovering that the pandemic had a more significant negative impact on the services trade than the goods trade.

[2] Kiyota (2022) examined how the pandemic affected global trade, using monthly level bilateral trade data from January 2000 and March 2021. The study found no evidence that changed trade significantly for major trading countries and Association of Southeast Asian Nations (ASEAN) Member States (AMS) after the pandemic began.

pointed out that the changes in trade structure caused by the pandemic in a single year was of a similar magnitude to changes otherwise typically seen over 5 years. Hayakawa and Mukunoki (2021) examined the effects of the COVID-19 pandemic on the trade of finished machinery products from January–June 2019 and January–June 2020, finding that, on one hand, the pandemic did not have a significant effect on demand for finished machinery products in importing countries. On the other, they found that the finished machinery trade was significantly hurt by higher rates of COVID-19 infection in countries exporting finished machinery products as well as countries exporting machinery parts to those countries.

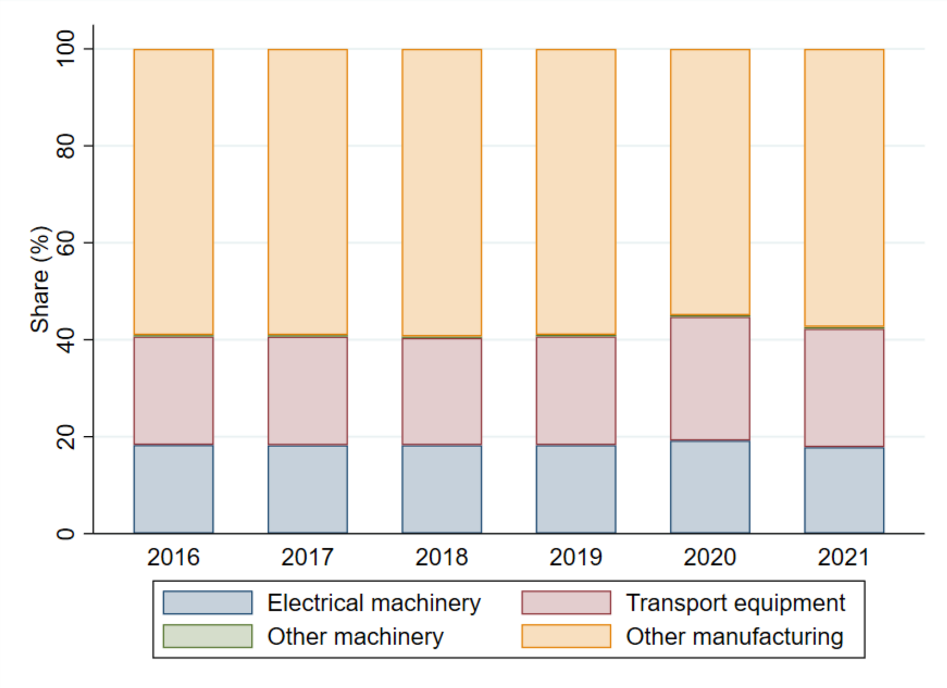
While these previous studies have made significant contributions to the literature, it remains unclear whether the patterns of machinery trade changed significantly after the pandemic. Did the pandemic cause a structural change in the pattern of machinery trade?[3] How did the relative importance of countries in the machinery trade change after the pandemic?

Figure 1 indicates that the share of machinery exports in total manufacturing exports was 41.0% in 2016, slightly increasing to 42.7% in 2021. Machinery exports were dominated by two categories: electrical machinery and transport equipment. The share of these two categories exceeded 40% of total manufacturing trade in 2021. Because machinery exports indicate a large share of manufacturing exports, it is essential to answer these questions for a deeper understanding of the impact of the pandemic on international trade.

[3] Structural breaks are defined as the break points in the time series of variables, while break points are defined as a significant shift in the mean or trend in the variables concerned.

Figure 1: Share of Machinery in Manufacturing Exports in the World

(%)



Notes: Manufacturing is defined as the Harmonized System (HS) categories 16 to 96. Machinery exports are 84 to 92, where 84 is electrical machinery and 85 is transport equipment.
Source: UN, UN Comtrade Database, https://comtradeplus.un.org/ (accessed 12/30/2022).

Based on this background, this study investigates whether the patterns of machinery trade changed significantly after the COVID-19 pandemic outbreak. It builds upon Kiyota (2022), which examined how total trade and the centrality of each country in world trade changed after the pandemic.[4] Following Kiyota (2022), this study focusses on trade and centrality; unlike Kiyota (2022), however, it focusses on the machinery trade.[5] It thus contributes to the literature by providing a more detailed analysis on the machinery trade and by employing formal statistical analysis to evaluate the significance of changes in the world machinery trade network after the pandemic began. Such disaggregated-level analysis should clarify whether there were shifts in the global value chain landscape as a result of the COVID-19 pandemic.

[4] After the COVID-19 pandemic, several studies employed the framework of network analysis to analyse trade patterns between countries. See, for example, Vidya and Prabheesh (2020), Antonietti et al. (2022), and Kiyota (2022).

[5] In this connection, Hayakawa and Mukunoki (2021) estimated a gravity model using data for 186 countries. One finding was that the negative impacts of the pandemic were particularly evident on exports from developing countries. Although they presented interesting findings, the network structure of trade was beyond the scope of their study.

This study may also have important policy implications. Understanding the vulnerability of supply chains helps policymakers identify sources of uncertainty in policymaking. It will attempt to clarify whether and which machinery products were vulnerable or resilient against the pandemic.

2. Methodology and Data

2.1. Network Analysis

This study employs the framework of network analysis to identify the relative importance of each country in world machinery trade and the framework of structural break to statistically detect structural change in the machinery trade as well as the centrality. In the framework of network analysis, each country is represented as a node, while the trade relationship between countries is represented as a link. The world machinery trade network thus is represented by nodes and links, which is called a graph.

There are three advantages to employing the framework of network analysis. First, the data requirement for the analysis is relatively low. Basically, only bilateral trade information is necessary. Second, trade data examine the current economic situation, as they are available monthly. Finally, the network analysis visualises the network of countries based on graph theory. It thus is helpful to capture the relative importance of each country in a simple manner.

The importance of each node is represented by centrality measures, including closeness centrality, which is based on the distance between nodes, and degree centrality, which is based on the number of links. However, because countries generally trade with many countries simultaneously, these centrality measures are not necessarily useful for the analysis of the world machinery trade network.

Several recent economic studies – such as Acemoglu et al. (2012) and Carvalho (2014) – utilised eigenvector centrality, which is also known as Bonacich centrality. However, this is not applicable to directed graphs. Therefore, it is not applicable to analysing the world machinery trade network because trade has a direction (i.e. from exporting countries to importing countries).

To overcome this problem, this study utilises PageRank centrality, which was originally developed to evaluate the ranking of webpages (Page et al. 1999). PageRank centrality is a variant of eigenvector centrality but has two advantages. First, like eigenvector centrality, PageRank centrality considers the number of edges (i.e. the trade relationship) that a node (i.e. a country) has as well as the number of edges that other directly connected nodes have. Indeed, as Kiyota (2023) showed, PageRank centrality is consistent with the index of upstreamness. Second, unlike eigenvector centrality, this centrality is applicable to a directed graph. Because trade has directions (i.e. from origin to destination), this is another desirable property for the analysis of trade.

Let the number of nodes be n. The adjacency matrix is denoted as A:

$$A = \begin{pmatrix} a_{11} & \cdots & a_{1j} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ a_{i1} & \cdots & a_{ij} & \cdots & a_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nj} & \cdots & a_{nn} \end{pmatrix}, \tag{1}$$

where:

$$a_{ij} = \begin{cases} 1, & \text{if there is a link from node } i \text{ to node } j; \\ 0, & \text{otherwise.} \end{cases} \tag{2}$$

Now, time dimension t is introduced. Let PageRank centrality be PR_{it} for country i at time t. Then, it is defined as:

$$PR_{it} = \psi \sum_{j=1}^{n} a_{ijt} \frac{PR_{jt}}{k_{jt}} + \chi \tag{3}$$

where ψ and χ are positive constants, and k_{jt} is the outdegree. In computing PageRank centrality, exports are used as a link weight. Equation (1) thus means that PageRank centrality for country i becomes high if (i) the number of country i's partners increases, (ii) country i's trade increases, and (iii) the PageRank for country i's partner increases. Conventionally, $\psi = 0.85$ and $\chi = 1$. To make comparisons between years, PageRank centrality is also adjusted, so its total equals 1.

2.2. Structural Break Analysis

Once the centrality measures are obtained, a structural break analysis is conducted to identify whether there are break points in the machinery trade and centrality measures in their time series. A break points is defined as a significant shift in mean or trend in the variables concerned. To detect a structural break, the test developed by Clemente, Montañés, and Reyes (1998) is employed that allows for estimation of two events within the observed history of a time series.[6] This allows investigation of whether countries experienced significant changes in trade and centrality during the sample period.

An outcome variable of country i is denoted as y_t (suppressing country i), where the outcome variable is either the log value of machinery exports or PageRank centrality. Consider that the time series of outcome y_t experiences one structural break during the sample. There are two types of models that can capture the structural break: an additive outlier (AO) model that captures a sudden change, and an innovational outlier (IO) model that captures a gradual shift in the mean of the series.[7]

The AO model consists of the following two steps. In the first step, the following regression equation is estimated:

$$y_t = \mu + \delta_1 DU_{1t} + \delta_2 DU_{2t} + \tilde{y}_t \tag{4}$$

where:

$$DU_{mt} = \begin{cases} 1, & \text{if } t > T_{bm}; \\ 0, & \text{otherwise,} \end{cases} \tag{5}$$

where $m = 1,\ 2$; T_{b1} and T_{b2} are the break points to be located by grid search; and $\tilde{y}_t$ denotes the residuals. In the second step, the residuals from this regression are used as the dependent variable for the following equation:

$$\tilde{y}_t = \sum_{\tau=1}^{d} \omega_{1\tau} DT_{b1,t-\tau} + \sum_{\tau=1}^{d} \omega_{2\tau} DT_{b2,t-\tau} + \alpha \tilde{y}_t + \sum_{\tau=1}^{d} \theta_\tau \Delta \tilde{y}_{t-\tau} + \varepsilon_t, \tag{6}$$

where:

$$DT_{bm,t} = \begin{cases} 1, & \text{if } t = T_{bm} + 1; \\ 0, & \text{otherwise,} \end{cases} \tag{7}$$

for $m = 1,\ 2$. The lag order d is also unknown. The second regression is estimated over feasible values of T_{bm} to search for the minimal t-statistic to test the autoregressive parameter $\alpha = 1$ (i.e. the strongest rejection of the unit root null hypothesis) for all the break time combinations, while d is determined by a set of sequential F-tests.[8] The significance

[6] There are several structural break tests. To compare the results with those of Kiyota (2022), the test developed by Clemente, Montañés, and Reyes (1998) is employed. In addition, for the test developed by Clemente, Montañés, and Reyes (1998), stata code is available (and thus easy to implement and replicate).

[7] One may be concerned that trade involves future contracts and thus cannot change suddenly. Because the IO model captures a graduate shift in the mean series, however, it captures the gradual change in futures contracts if that is the case.

[8] The maximum lag number is set as 12 to reduce the computational burden and to account for seasonality (i.e.

level of this minimal t-statistic is investigated based on the critical values provided by Perron and Vogelsang (1992).

In contrast, the IO model is based on a one-step procedure. The following regression equation is thus estimated:

$$
\begin{aligned}
y_t = \mu + \delta_1 DU_{1t} + \delta_2 DU_{2t} + \phi_1 DT_{b1,t} + \phi_2 DT_{b2,t} \\
+\alpha y_{t-1} + \sum_{\tau=1}^{d} \theta_\tau \Delta y_{t-\tau} + \varepsilon_t.
\end{aligned} \tag{8}
$$

As in the AO model, the regression equation is estimated over feasible values of T_{bm} to search for the minimal t-statistic to test the autoregressive parameter $\alpha = 1$ (i.e. the strongest rejection of the unit root null hypothesis) for all the break time combinations, while d is determined by a set of sequential F-tests.

Note that it is necessary to choose some trimming values, because the test is not defined at the limits of the sample (Clemente, Montañés, and Reyes, 1998). Banerjee, Lumsdaine, and Stock (1992) suggested using a window $(0.15,\ 0.85)$. However, Perron and Vogelsang (1992) pointed out that this choice is arbitrary. To adapt the largest window possible in both the theoretical derivations and the empirical applications, following Zivot and Andrews (1992), the values $((d+2)/T, (T-1)/T)$ are therefore set.[9]

2.3. Hypothesis

Although the COVID-19 pandemic is ongoing, most of the strict measures – including lockdowns – were introduced in early 2020. Therefore, significant changes in the patterns of the machinery trade, if any, are assumed to appear in 2020. This study thus focusses on 2020 and examines whether a break point can be found in the patterns of the machinery trade in 2020. The hypothesis is:

If the COVID-19 pandemic has a significantly negative impact on the patterns of machinery exports, significantly negative coefficients in 2020 will be found.

Note that the focus of the analysis is to identify the timing of the structural change. Although investigating the sources of the structural change is beyond the scope of this study,

$d = 12$). Note that there is no intercept because the mean of $\tilde{y}_t$ is zero.

[9] This interval was also adopted by Perron and Vogelsang (1992) and Lumsdaine and Papell (1997). It is technically difficult to set the interval and lag order simultaneously. As a shortcut, the maximum lag order (i.e. $d = 12$) is used for the interval while determining the lag order by a set of sequential F-test.

possible factors for further research are discussed. It is also important to note that there were several other shocks during the sample period (i.e. January 2016–March 2022). If those shocks are more significant than the pandemic, those shocks are the break points. The question is whether the pandemic had more significant effects on exports than other shocks.

2.4. Data

Monthly export data from January 2016 to March 2022 (75 months) are mainly used, obtained from the UN Comtrade Database. Monthly imports are valued at the CIF price (i.e. cost, insurance, and freight price) while monthly exports are valued at the FOB (i.e. free on-board price). To exclude the effects of the freight charges and shipping insurance, exports rather than imports are used.[10]

Note that the availability of monthly-level trade data varies amongst countries. Table 1 summarises the data availability for major machinery-exporting countries and Association of Southeast Asian (ASEAN) Member States (AMS). Because monthly export data are not available for China between October 2012 and December 2015, the period after 2015 is the focus.

Table 1: Sample Period in the United Nations Comtrade Database

		Start	End	*T*	Not available
Major countries	CHN	2016m1	2022m3	75	2012m10-2015m12
	DEU	2010m1	2022m3	147	
	HKG	2010m1	2022m3	147	
	JPN	2010m1	2022m3	147	
	USA	2010m1	2022m3	147	
ASEAN	BRN	2015m1	2020m12	72	2014m1-2014m12
	IDN	2015m1	2022m3	87	2013m9 & 2014m11-2014m12
	KHM	2015m1	2020m12	72	2010m1-2014m12 & 2021m1-
	LAO	2015m1	2020m12	72	2010m1-2014m12 & 2021m1-
	MMR	2011m1	2021m12	132	2010m1-2010m12 & 2022m1-
	MYS	2014m8	2021m12	89	2014m7 & 2022m1
	SGP	2013m5	2021m6	98	2013m4 & 2021m7-
	VNM	2015m1	2021m12	84	2010m1-2014m12 & 2022ml-
	PHL				2019m6
	THA				2019m10

ASEAN = Association of Southeast Asian Nations, BRN = Brunei Darussalam, CHN = China, DEU = Germany, HKG = Hong Kong, IDN = Indonesia, JPN = Japan, KHM = Cambodia, LAO = Lao People's Democratic Republic, m = month, MMR = Myanmar, MYS = Malaysia, PHL = Philippines, SGP = Singapore, THA = Thailand, USA = United States, VNM = Viet Nam.
Source: UN, UN Comtrade Database, https://comtradeplus.un.org/ (accessed 12/30/2022).

[10] As a robustness check, import data are also utilised, as discussed later.

Following Ando, Kimura, and Obashi (2022), two-digit classifications of the Harmonized System (HS) codes between 84 and 92 are used: general machinery (HS84), electrical machinery (HS85), transport equipment (HS86–89), and precision machinery (HS90–92). The classifications are aggregated, and then machinery trade as a whole is used as a benchmark.

Five major machinery-exporting countries are the focus: China, Germany, Hong Kong, Japan, and the US, because these countries have been ranked in the top five machinery exporters for most of the years between 2016 and 2021. In 2021, these five countries accounted for over 50% of world machinery exports.[11]

Note that the HS classification codes were revised several times during the sample period. While the importance of tracing the same product throughout the period is acknowledged, it is difficult to do so at the two-digit level because the classification changes occurred at the detailed product level. In addition, for machinery products, most of the products are classified within the same two-digit level, although some of the electrical machinery products are classified into different categories. This study continues to use the HS84–92 codes.

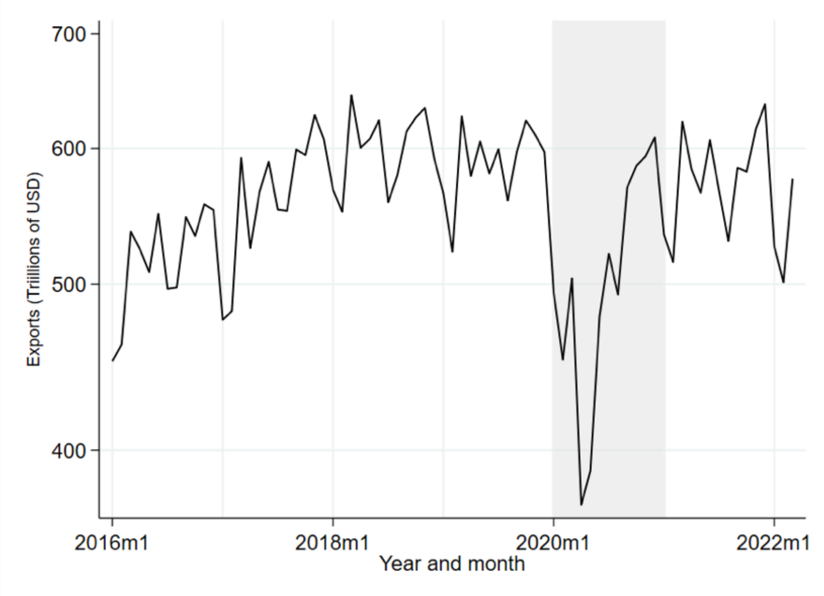
Note also that the data had to be trimmed for the structural break analysis. As mentioned previously, the $((k+2)/T, (T-1)/T)$ interval is used, where $k = 12$ and $T = 75$. This means that the interval is (14, 74), which dropped 10% of the sample (i.e. the first 13 months at the beginning of the sample period and the last month of the sample). Because the pandemic started in March 2020 $(t = 51)$, there are basically $23(= 74 - 51)$ months after the pandemic outbreak. The analysis thus has enough observations.

2.5. Continuing Export Countries

Figures 2 and 3 present the changes in the total value of machinery exports and total number of destination countries. The total value indicates the sum of all of the countries' exports, while the total number of destination countries indicates the number of origin countries multiplied by the number of destination countries. Two findings are highlighted. First, the value of machinery exports declined when the pandemic began in March 2020, but then it showed a quick recovery from mid-2020. Second, in contrast, the number of destination countries declined around March 2020 and then continued to fall with some fluctuations after.

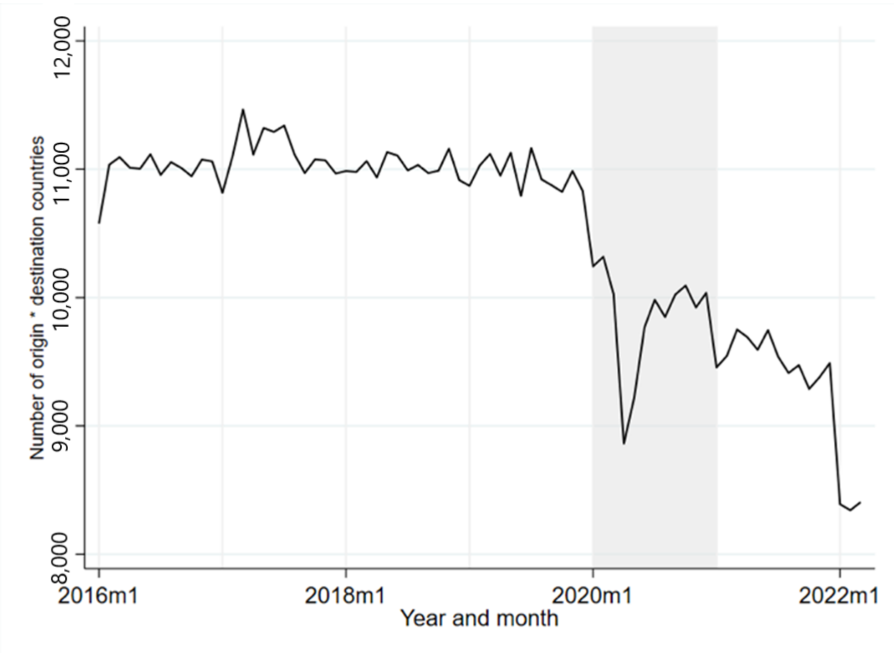
[11] South Korea also ranked in the top five for some years during this period. However, South Korean export data are not available from 2020 at the monthly level in the UN Comtrade Database.

Figure 2: Value of Machinery Exports
($ trillion)



M = month.
Notes: Total value of machinery exports indicates the aggregation of export values for each country. The grey area indicates 2020.
Source: UN, UN Comtrade Database, https://comtradeplus.un.org/ (accessed 12/30/2022).

Figure 3: Destination Countries of Machinery Exports
(number)



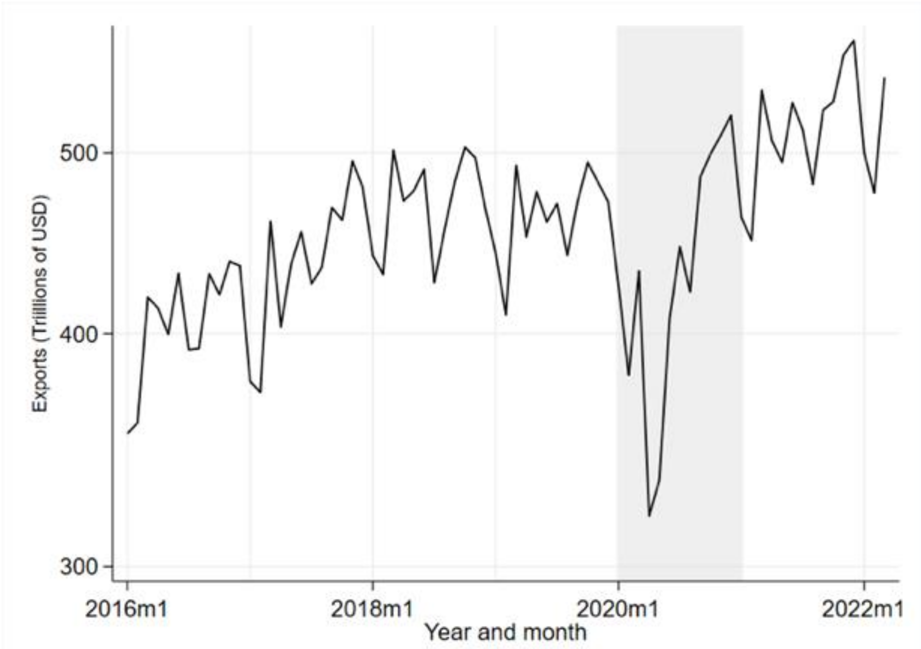
M = month.
Notes: The total number of destination countries indicates the aggregation of export destination countries for each country. The grey area indicates 2020.
Source: UN, UN Comtrade Database, https://comtradeplus.un.org/ (accessed 12/30/2022).

Monthly export data are not available from 2021 for some AMS such as Cambodia, the Lao People's Democratic Republic, and Viet Nam. Chinese monthly export data are not available from October 2012 to December 2015. Because PageRank centrality is affected by the presence or absence of trade between countries, the data availability can affect the results.

To address this issue, the sample is restricted to countries that continued to export machinery products to at least one country throughout January 2016 to March 2022. In 2019 (i.e. before the pandemic), there are about 117 exporting countries (monthly average). The number of continuing export countries is 48. In 2019, the share of these continuing export countries is 58.9% of total machinery exports in the world.

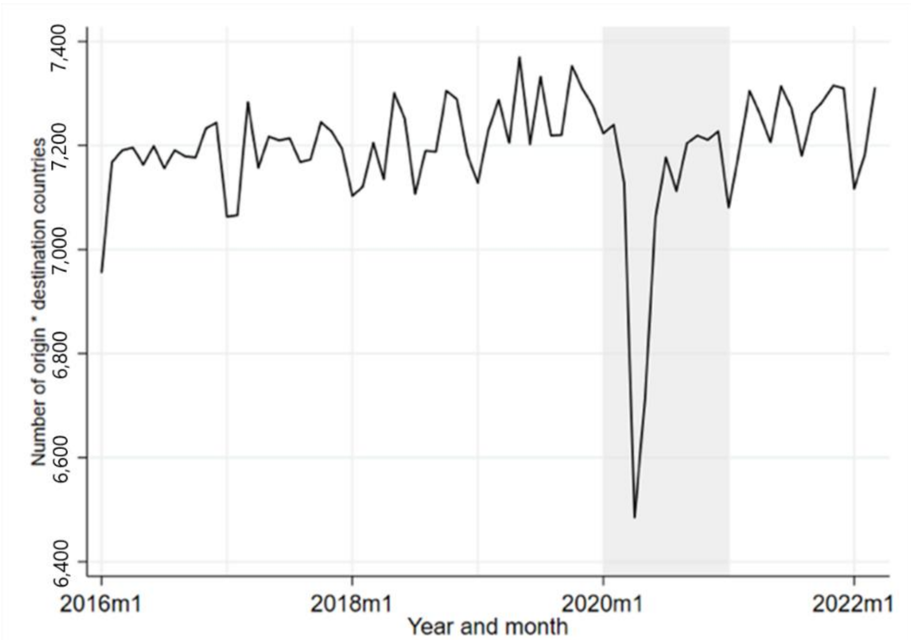
Figures 4 and 5 present the changes in the total value of machinery exports and total number of destination countries for these countries. There are two notable findings. First, like the results of all exporting countries (Figure 2), although the value of machinery exports declined when the pandemic started around March 2020, it showed a quick recovery from mid-2020. Second, unlike the results of all machinery-exporting countries (Figure 3), the number of export destination countries did not decline significantly except for the period between March 2020 and April 2020. These results imply that the decline in the number of destination countries in Figure 3 is attributable to data availability.

Figure 4: Value of the Machinery Exports in the World – Continuing Export Countries
($ trillion)



M = month.
Notes: Total value of machinery exports indicates the aggregation of export values for each country. The grey area indicates 2020.
Source: UN, UN Comtrade Database, https://comtradeplus.un.org/ (accessed 12/30/2022).

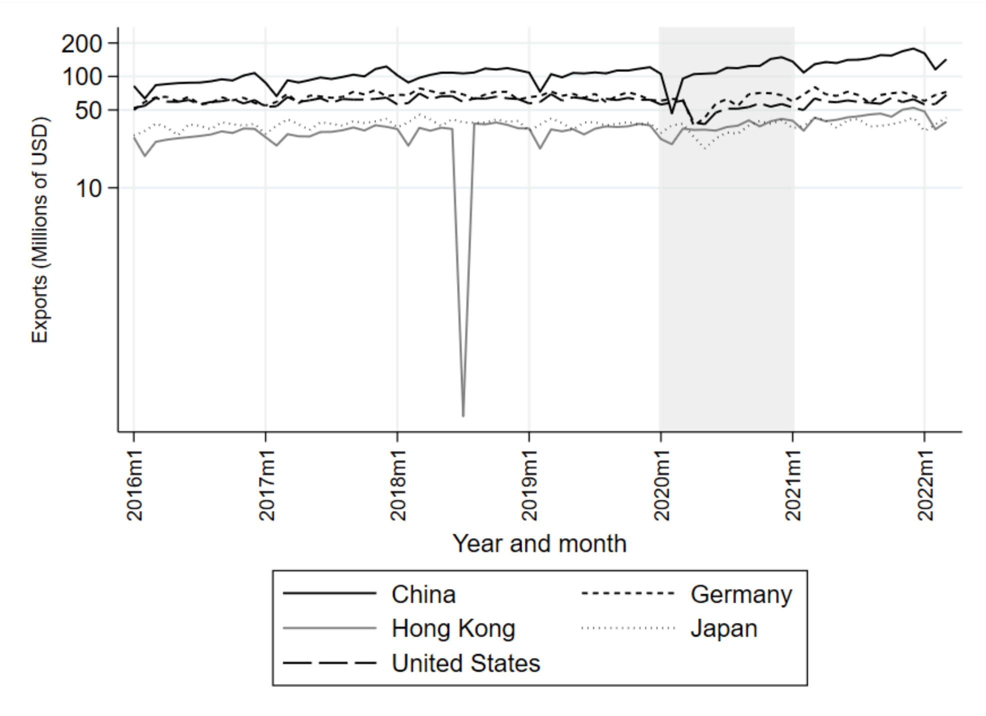
Figure 5: Destination Countries of Machinery Exports – Continuing Export Countries
(number)



m = month.
Notes: Total number of destination countries indicates the aggregation of export destination countries for each country. The grey shaded area indicates 2020.
Source: UN, UN Comtrade Database, https://comtradeplus.un.org/ (accessed 12/30/2022).

Figure 6 presents machinery exports for the five major machinery-exporting countries from January 2016 to March 2022. There are three notable findings. First, machinery exports declined significantly in the early 2020 for these countries. Second, Hong Kong's exports dropped significantly in mid-2018, because the exports of many machinery products including electrical machinery and transport equipment are missing for July 2018 in the UN Comtrade Database. Although this may be regarded as an outlier, caution is needed in interpreting the results of Hong Kong. Third, it is difficult tell which month-year indicates the break points. In the next section, an econometric analysis is employed to identify the break points in a precise manner.

Figure 6: Machinery Exports for Major Machinery-Exporting Countries
($ million)



M = month.
Notes: Machinery exports are from HS84 to 92, where 84 is electrical machinery and 85 is transport equipment. The grey area indicates 2020.
Source: UN, UN Comtrade Database, https://comtradeplus.un.org/ (accessed 12/30/2022).

3. Estimation Results

3.1. Structural Breaks in Machinery Exports

Whether a structural break is observed in exports in 2020 is first investigated. Equations (4) and (6) are estimated for the AO model, and equation (8) is estimated for the IO model, using machinery export data as an outcome variable. Because the log is used for the dependent variable, the coefficients are interpreted as the percentage change of the dependent variable. Table 2 presents the estimation results for the major machinery-exporting countries. Figures A1.1–A1.5 in Appendix 1 indicate the break points to visually check them.

Table 2: Break Points of Machinery Exports – Major Machinery-Exporting Countries

AO model					
	CHN	DEU	HKG	JPN	USA
Break point 1	2018m12	**2020m1**	2018m5	**2020m2**	**2020m1**
	0.016	**-0.123*****	-0.033	**-0.111*****	**-0.110*****
	(0.527)	**(-5.874)**	(-0.321)	**(-6.479)**	**(-6.603)**
Break point 2	2019m12	2020m6	2021m4	2020m8	2020m7
	0.076**	0.121***	0.178	0.113***	0.079***
	(2.558)	(5.549)	(1.524)	(6.188)	(4.484)
IO model					
	CHN	DEU	HKG	JPN	USA
Break point 1	2019m1	**2020m2**	2018m6	**2020m2**	**2020m2**
	-0.007	**-0.239*****	-0.002	**-0.134*****	**-0.171*****
	(-0.548)	**(-7.291)**	(-0.113)	**(-5.910)**	**(-9.187)**
Break point 2	2020m1	2020m7	2020m7	2020m8	2020m7
	0.043***	0.225***	0.109***	0.126***	0.147***
	(3.653)	(6.963)	(5.519)	(5.415)	(7.323)

AO = additive outlier, CHN = China, DEU = Germany, HKG = Hong Kong, IO = innovational outlier, JPN = Japan, m = month, USA = United States.
Notes: The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The figures in parentheses are t-statistics. The break points indicate the estimated year and month when the structural breaks are identified. Bold letters indicate significantly negative coefficients in 2020, while grey indicates significantly positive coefficients.
Source: UN, UN Comtrade Database, https://comtradeplus.un.org/ (accessed 12/30/2022).

Three findings emerged from the AO model results. First, for China and Hong Kong, the results indicate no significantly negative coefficient in 2020. This implies that the hypothesis is rejected. Machinery exports in these countries were resilient to the shocks from the COVID-19 pandemic. This result is consistent with Ando, Kimura, and Obashi (2021) and Ando, Kimura, and Yamanouchi (2022), which found resilience of the machinery trade in East Asia during the pandemic period.

Second, in contrast, the results indicate significantly negative coefficients in January 2020 for Germany and the US and in February 2020 for Japan. This result suggests that, for Germany, Japan, and the US, the hypothesis is not rejected. The COVID-19 pandemic had a significant impact on machinery exports of these three countries. Yet significantly positive coefficients are then confirmed in mid-2020 for these three countries. Note that the absolute values of the coefficients indicate similar magnitudes: –0.123 and 0.121 for Germany, –0.111 and 0.113 for Japan, and –0.110 and 0.079 for the US. Noting that the coefficients indicate the percentage change of the dependent variable, this implies that the significant drops in exports were mostly offset by their increases in mid-2020. These findings are also basically in line with Ando, Kimura, and Obashi (2021) and Ando, Kimura, and Yamanouchi (2022).

The results of the IO model are similar to those of the AO model. One notable difference is that significantly positive coefficients in 2020 are confirmed for China. This implies that that the COVID-19 pandemic positively affected the machinery exports of China, perhaps due to positive demand shocks.

One may be concerned about a lag between business contracts and actual transactions of the products (i.e. trade), meaning that the effects of the pandemic would not appear instantaneously. Rather, the effects did appear with some lags, which in turn implies that the effects appeared in 2021 rather than in 2020. However, Table 2 does not indicate any significant break points in 2021. The effects of contracts, if any, do not have any significant effects on the results.

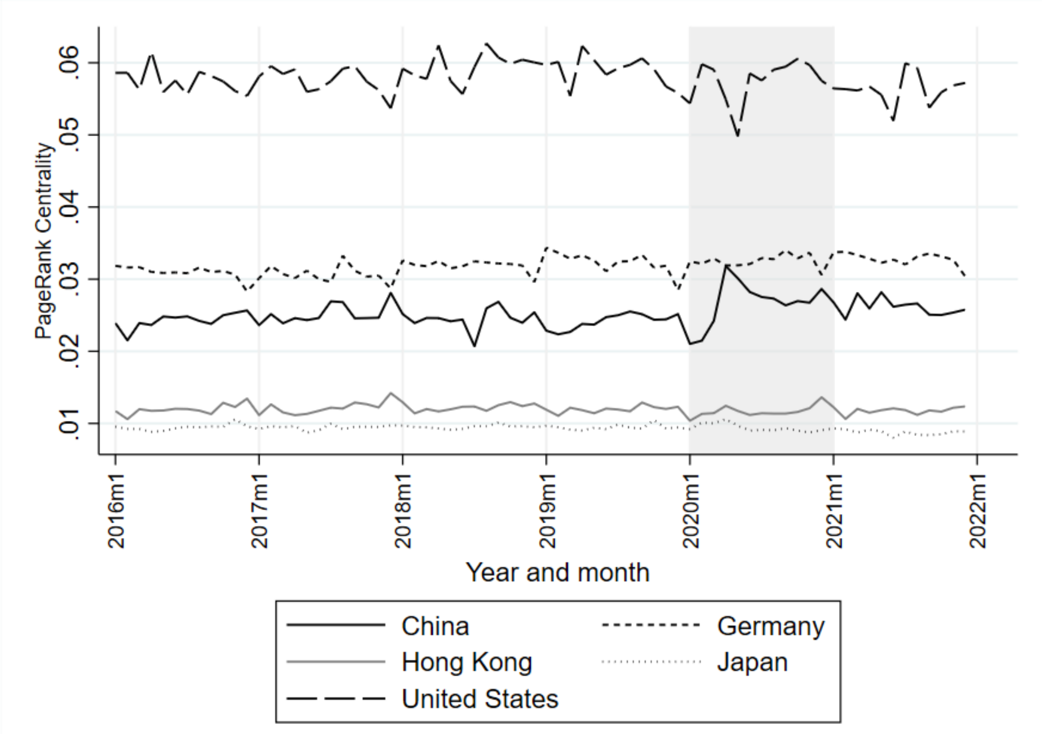
In sum, the impacts of the COVID-19 pandemic on machinery exports were basically not negative but positive in China and Hong Kong. The impacts on Germany, Japan, and the US were significantly negative, but they were temporal as both negative and positive break points are observed in 2020. These results together suggest that machinery exports were basically resilient for these five countries.

3.2. Structural Breaks in Centrality

Machinery exports were basically resilient for major machinery-exporting countries. Now, equations (4) and (6) are estimated for the AO model, and equation (8) is estimated for the IO model, using PageRank centrality as an outcome variable for these countries.

Figure 7 presents the changes in PageRank centrality between January 2016 and March 2022. Table 3 presents the estimation results for PageRank centrality. Figures A1.6–A1.10 in Appendix 1 indicate the break points to visually check them.

Figure 7: Centrality of Machinery in Manufacturing Exports in the World – Major Machinery-Exporting Countries



M = month.
Notes: Machinery exports are from HS84 to 92, where 84 is electrical machinery and 85 is transport equipment. The grey area indicates 2020.
Source: UN, UN Comtrade Database, https://comtradeplus.un.org/ (accessed 12/30/2022).

While the AO model indicates no significant coefficients in 2020 for these countries, the IO model indicates a significantly negative coefficient in 2020 for Japan. This result supports the hypothesis, implying that the COVID-19 pandemic had significantly negative impacts on the relative importance of Japan in the world machinery trade network. This result is different from the result of Japan in overall exports. Indeed, Kiyota (2022) employed the same framework and found no significant coefficient after the COVID-19 pandemic outbreak, using overall trade data. This, in turn, suggests that the patterns of the machinery trade are slightly different from those of overall trade.

Table 3: Break Points of the Centrality of Machinery Exports – Major Machinery-Exporting Countries

AO model					
	CHN	DEU	HKG	JPN	USA
Break point 1	2018m5	2017m10	2017m10	2020m2	2018m2
	-0.031	0.036**	0.014	-0.022	0.029*
	(-1.268)	(2.437)	(0.655)	(-1.644)	(2.104)
Break point 2	2019m12	2019m10	2019m11	2021m3	2019m11
	0.082***	0.012	-0.037**	-0.069***	-0.044***
	(3.717)	(1.149)	(-2.475)	(-3.863)	(-3.795)
IO model					
	CHN	DEU	HKG	JPN	USA
Break point 1	2018m6	2019m11	2017m11	**2020m3**	2017m11
	-0.022	0.005	0.009	**-0.040*** **	0.029*
	(-1.100)	(0.561)	(0.362)	**(-3.255)**	(1.836)
Break point 2	2020m1	Not detected	2018m11	2021m4	2019m9
	0.082***		-0.045**	-0.057***	-0.043***
	(3.826)		(-2.517)	(-2.993)	(-3.436)

AO = additive outlier, CHN = China, DEU = Germany, HKG = Hong Kong, IO = innovational outlier, JPN = Japan, m = month, USA = United States.
Notes: The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The figures in parentheses are t-statistics. The break points indicate the estimated year and month when the structural breaks are identified. Bold letters indicate significantly negative coefficients in 2020, while grey indicates significantly positive coefficients.
Source: UN, UN Comtrade Database, https://comtradeplus.un.org/ (accessed 12/30/2022).

A concern may be that there is a lag between business contracts and actual transactions of the products (i.e. trade), which suggests that the effects appear with some lags. However, Table 3 indicates significantly negative coefficients only for Japan in both the AO and IO models.

The relative importance of top five machinery-exporting countries – except for Japan – did not change when the COVID-19 pandemic started. In the next section, whether this pattern is confirmed is explored at more disaggregated levels and for AMS.[12]

[12] The break points of machinery imports and centrality for these five countries are also estimated, finding positive coefficients for imports and negative coefficients for centrality in 2020. The results are presented in Tables A2.1 and A2.2 in Appendix 2.

4. Further Analysis

4.1. Electrical Machinery and Transport Equipment

The previous section presents the results of all machinery exports, covering the HS categories 84 to 92. However, the results differ between sectors. For example, Ando, Kimura, and Obashi (2021) found that the negative impacts of the COVID-19 pandemic on exports were larger in the transport equipment industry than in other machinery industries. This section thus presents a disaggregated-level analysis, focussing on two major machinery categories: electrical machinery and transport equipment.

Tables 4 and 5 present the estimation results for exports of electrical machinery and transport equipment, respectively.[13] Two findings are highlighted. First, for exports of electrical machinery, the results in Table 4 are similar to the results in Table 2. One notable difference is that a significantly negative coefficient is confirmed before 2020 for Japan in the IO model. Although the month is sometimes different, the same patterns are confirmed in Tables 2 and 4. This, in turn, means that the export patterns of machinery goods as a whole were basically the same as those of electrical machinery.

[13] The break points for Hong Kong cannot be estimated because the exports of electrical machinery and transport equipment are missing for July 2018, as mentioned previously.

Table 4: Break Points of Electrical Machinery Exports – Major Machinery-Exporting Countries

AO model	CHN	DEU	HKG	JPN	USA
Break point 1	2018m12	**2020m1**	Not available	**2020m2**	**2020m1**
	0.024	**-0.062*** **		**-0.046*** **	**-0.050*** **
	(0.737)	**(-4.234)**		**(-2.976)**	**(-4.853)**
Break point 2	2019m12	2020m7		2020m8	2020m9
	0.076**	0.105***		0.093***	0.074***
	(2.441)	(6.750)		(5.697)	(6.638)
IO model	**CHN**	**DEU**	**HKG**	**JPN**	**USA**
Break point 1	2019m1	**2020m2**	Not available	2019m11	**2020m2**
	-0.006	**-0.123*** **		-0.030**	**-0.091*** **
	(-0.444)	**(-6.115)**		(-2.116)	**(-5.495)**
Break point 2	2020m1	2020m7		2020m7	2020m8
	0.039***	0.172***		0.057***	0.124***
	(2.902)	(6.669)		(3.237)	(5.593)

AO = additive outlier, CHN = China, DEU = Germany, HKG = Hong Kong, IO = innovational outlier, JPN = Japan, m = month, USA = United States.
Notes: The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The figures in parentheses are t-statistics. The break points indicate the estimated year and month when the structural breaks are identified. Bold letters indicate significantly negative coefficients in 2020, while grey indicates significantly positive coefficients.
Source: UN, UN Comtrade Database, https://comtradeplus.un.org/ (accessed 12/30/2022).

Second, for transport equipment, the results in Table 5 are also very similar to the results in Table 2. A notable difference is that the significantly positive coefficient is confirmed after 2019 for China in the AO model. The month is sometimes different, but essentially, the same patterns are confirmed in Tables 2 and 5. This, in turn, means that the export patterns of machinery goods as a whole were also basically the same as those of transport equipment.

Table 5. Break Points of Transport Equipment Exports – Major Machinery-Exporting Countries

AO model	CHN	DEU	HKG	JPN	USA
Break point 1	2019m11 -0.052 (-1.612)	**2020m1** **-0.222***** **(-5.820)**	Not available	**2020m3** **-0.257***** **(-9.260)**	**2020m1** **-0.225***** **(-7.835)**
Break point 2	2020m8 0.231*** (6.677)	2020m6 0.186*** (4.683)		2020m7 0.207*** (7.173)	2020m7 0.118*** (3.902)

IO model	CHN	DEU	HKG	JPN	USA
Break point 1	2019m12 -0.160*** (-3.549)	**2020m2** **-0.453***** **(-7.692)**	Not available	**2020m2** **-0.309***** **(-9.420)**	**2020m2** **-0.414***** **(-12.102)**
Break point 2	2020m7 0.325*** (4.551)	2020m6 0.398*** (7.222)		2020m7 0.159*** (5.551)	2020m7 0.282*** (6.529)

AO = additive outlier, CHN = China, DEU = Germany, HKG = Hong Kong, IO = innovational outlier, JPN = Japan, m = month, USA = United States.
Notes: The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The figures in parentheses are t-statistics. The break points indicate the estimated year and month when the structural breaks are identified. Bold letters indicate significantly negative coefficients in 2020, while grey indicates significantly positive coefficients.
Source: UN, UN Comtrade Database, https://comtradeplus.un.org/ (accessed 12/30/2022).

Tables 6 and 7 present the estimation results for PageRank centrality of exports of electrical machinery and transport equipment, respectively. Table 6 indicates significantly negative coefficients in 2020 for Japan – February 2020 in the AO model and March 2020 in the IO model. This result implies that the relative importance of Japan in the network of electrical machinery exports declined during the pandemic period.

Table 6: Break Points of the Centrality of Electrical Machinery Exports – Major Machinery-Exporting Countries

AO model					
	CHN	DEU	HKG	JPN	USA
Break point 1	2019m12	2017m4	Not	2018m9	2018m2
	0.136***	0.050**	available	0.007	0.044
	(7.346)	(2.227)		(0.496)	(1.671)
Break point 2	2021m7	2020m10		**2020m2**	2018m10
	-0.098***	0.044***		**-0.040*****	-0.004
	(-3.562)	(4.056)		**(-3.075)**	(-0.193)
IO model					
	CHN	DEU	HKG	JPN	USA
Break point 1	2020m1	2019m11	Not	2018m10	2017m11
	0.113***	0.015	available	0.009	0.069
	(4.895)	(1.554)		(0.890)	(1.120)
Break point 2	2021m7	Not		**2020m3**	2018m11
	-0.093***	detected		**-0.041*****	0.039
	(-3.447)			**(-3.686)**	(1.592)

AO = additive outlier, CHN = China, DEU = Germany, HKG = Hong Kong, IO = innovational outlier, JPN = Japan, m = month, USA = United States.
Notes: The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The figures in parentheses are t-statistics. The break points indicate the estimated year and month when the structural breaks are identified. Bold letters indicate significantly negative coefficients in 2020, while grey indicates significantly positive coefficients.
Source: UN, UN Comtrade Database, https://comtradeplus.un.org/ (accessed 12/30/2022).

Table 7 shows that, for transport equipment, significantly negative coefficients in 2020 for Japan and the US are confirmed in both the AO and IO models. The decline in the centrality of machinery exports for Japan may have been due to the decline in the centrality of transport equipment exports. This finding is in line with Ando, Kimura, and Obashi (2021), which found that the negative impacts of the COVID-19 pandemic on exports were larger in the transport equipment industry than in other machinery industries.

Table 7: Break Points of the Centrality of Transport Equipment Exports, Major Machinery-Exporting Countries

AO model					
	CHN	DEU	HKG	JPN	USA
Break point 1	2018m12	2018m10	Not available	2019m9	**2020m1**
	-0.128***	0.018		0.059*	**-0.066***
	(-3.333)	(0.992)		(1.861)	**(-1.778)**
Break point 2	2019m12	2019m10		**2020m6**	2020m6
	0.081**	0.016		**-0.143***	0.106**
	(2.165)	(0.924)		**(-4.231)**	(2.739)
IO model					
	CHN	DEU	HKG	JPN	USA
Break point 1	2018m11	2018m11	Not available	2019m10	2020m6
	-0.121***	0.044**		0.089**	0.144**
	(-3.232)	(2.333)		(2.491)	(2.516)
Break point 2	2020m1	2019m11		**2020m5**	**2020m10**
	0.101***	0.029*		**-0.167***	**-0.122***
	(2.934)	(1.922)		**(-3.733)**	**(-1.986)**

AO = additive outlier, CHN = China, DEU = Germany, HKG = Hong Kong, IO = innovational outlier, JPN = Japan, m = month, USA = United States.
Notes: The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The figures in parentheses are t-statistics. The break points indicate the estimated year and month when the structural breaks are identified. Bold letters indicate significantly negative coefficients in 2020, while grey indicates significantly positive coefficients.
Source: UN, UN Comtrade Database, https://comtradeplus.un.org/ (accessed 12/30/2022).

5. Results for ASEAN Member States

Thus far, a decline in the relative importance of major machinery-exporting countries in the global machinery trade network has been confirmed. This may have been due to the increases in the relative importance of other countries, particularly in ASEAN where the machinery trade is active. This subsection runs the same regressions as those in Section 3, focussing on AMS. Due to the limited availability of data, the period between January 2015 and June 2021 is the focus for Indonesia, Malaysia, Myanmar, Singapore, and Viet Nam.[14] To save space, the results of PageRank centrality are presented; the results for exports are presented in the Appendix.

[14] In the monthly level UN Comtrade Database, data for June 2019 are not available for the Philippines, and October 2019 data are not available for Thailand.

Tables 8 and 9 present the estimation results for machinery exports and PageRank centrality, respectively, for AMS. In Table 8, Indonesia presents both negative and positive coefficients in 2020, like the results of Germany, Japan, and the US in Table 2. Malaysia, Singapore, and Viet Nam indicate positive coefficients in 2020, similar to the results of China and Hong Kong in Table 2. Myanmar does not indicate any significant break points. Overall, these results indicate that the results of AMS are like those of major machinery-exporting countries.

Table 8: Break Points of Machinery Exports – ASEAN Member States

AO model					
	IDN	MMR	MYS	SGP	VNM
Break point 1	**2020m1**	2016m6	2017m5	2016m12	2017m5
	-0.084***	-0.449**	0.104***	0.051***	0.162***
	(-3.371)	(-2.143)	(7.125)	(4.606)	(7.722)
Break point 2	2020m7	2017m2	2020m3	2020m7	2020m3
	0.148***	0.401***	0.041***	0.067***	0.106***
	(5.089)	(2.878)	(2.751)	(6.021)	(4.937)
IO model					
	IDN	MMR	MYS	SGP	VNM
Break point 1	**2020m2**	2017m3	2017m6	2020m4	2020m4
	-0.204***	0.350***	0.060**	0.038***	0.079***
	(-5.862)	(3.285)	(2.341)	(3.747)	(3.376)
Break point 2	2020m7	2020m3	2020m4		
	0.309***	-0.126	0.063***		
	(6.362)	(-1.249)	(4.493)		

AO = additive outlier, IDN = Indonesia, IO = innovational outlier, m = month, MMR = Myanmar, MYS = Malaysia, SGP = Singapore, VNM = Viet Nam.
Notes: The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The figures in parentheses are t-statistics. The break points indicate the estimated year and month when the structural breaks are identified. Bold letters indicate significantly negative coefficients in 2020, while grey indicates significantly positive coefficients.
Source: UN, UN Comtrade Database, https://comtradeplus.un.org/ (accessed 12/30/2022).

In Table 9, significantly negative coefficients are noted for Indonesia (April 2020 in the AO model and May 2020 in the IO model), Malaysia (July 2020 in the AO model and June 2020 in the IO model), and Singapore (February 2020 in the AO model and March 2020 in the IO model). These results imply that the decline in the relative importance of these three AMS in machinery exports. These results are similar to the results of Japan in Table 3.

Table 9: Break Points of the Centrality of Machinery Exports – ASEAN Member States

AO model					
	IDN	MMR	MYS	SGP	VNM
Break point 1	2019m1	2017m12	2017m11	2016m7	2017m4
	-0.006	-0.018**	-0.096***	-0.033	-0.064**
	(-0.391)	(-2.628)	(-6.098)	(-0.703)	(-2.465)
Break point 2	**2020m4**	2019m6	**2020m7**	**2020m2**	2018m3
	-0.050**	0.010	**-0.048****	**-0.080****	0.060***
	(-2.787)	(1.434)	**(-2.390)**	**(-2.531)**	(2.691)
IO model					
	IDN	MMR	MYS	SGP	VNM
Break point 1	2019m2	2018m1	2017m12	2016m8	2017m5
	-0.018	-0.033***	-0.140***	-0.027	-0.092***
	(-1.374)	(-3.714)	(-3.004)	(-0.838)	(-3.575)
Break point 2	**2020m5**	2019m7	**2020m6**	**2020m3**	2018m4
	-0.042**	0.021***	**-0.060****	**-0.093*****	0.097***
	(-2.501)	(3.285)	**(-2.424)**	**(-3.898)**	(4.231)

AO = additive outlier, IDN = Indonesia, IO = innovational outlier, m = month, MMR = Myanmar, MYS = Malaysia, SGP = Singapore, VNM = Viet Nam.
Notes: The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The figures in parentheses are t-statistics. The break points indicate the estimated year and month when the structural breaks are identified. Bold letters indicate significantly negative coefficients in 2020, while grey indicates significantly positive coefficients.
Source: UN, UN Comtrade Database, https://comtradeplus.un.org/ (accessed 12/30/2022).

These results have two important implications. First, the decline in the relative importance of Japan in the global machinery trade network is not attributed to the increases in the relative importance of these AMS. Second, the decline in the relative importance of Japan may have been due to the close relationship with these AMS, because PageRank centrality reflects not only the importance of Japan but also that of its export partner countries. To investigate this issue, the same structural break analysis is conducted, replacing the log of the value of exports with the log of the number of destination countries.

Tables 10 and 11 present the estimated break points for the number of destination countries for the major machinery-exporting countries and AMS, respectively. Two findings are highlighted. First, Table 10 indicates significantly negative coefficients in 2020 for Hong Kong (November 2020 in the IO model) and the US (January 2020 in the AO model). These imply that the number of destination countries fell for Hong Kong and the US after the pandemic outbreak. Second, Japan does not indicate significantly negative coefficients in either the AO or IO model. Finally, Table 11 presents significantly negative coefficients for four out of five AMS (i.e. Indonesia, Malaysia, Myanmar, and Singapore). This suggests that the number of destination countries also decreased for these AMS after the pandemic outbreak.

Table 10: Break Points of the Number of Machinery Export Destination Countries – Major Machinery-Exporting Countries

AO model					
	CHN	DEU	HKG	JPN	USA
Break point 1	2019m11	2017m9	2017m7	2018m2	2017m11
	-0.008**	-0.013**	-0.011	0.000	0.004
	(-2.386)	(-2.517)	(-0.239)	(0.068)	(0.919)
Break point 2	2020m4	2018m6	2018m5	2019m11	**2020m1**
	0.003	0.024***	-0.009	-0.008**	**-0.011*** **
	(0.965)	(6.225)	(-0.281)	(-2.477)	**(-3.594)**
IO model					
	CHN	DEU	HKG	JPN	USA
Break point 1	2019m12	2017m10	2018m6	2019m12	2018m7
	-0.015***	-0.016***	0.005	-0.011***	0.015***
	(-3.581)	(-2.821)	(1.263)	(-3.184)	(3.165)
Break point 2	2020m5	2018m6	**2020m11**	2021m5	2019m2
	0.004	0.027***	**-0.008** **	-0.003	-0.020***
	(1.036)	(4.911)	**(-2.184)**	(-0.747)	(-4.071)

AO = additive outlier, CHN = China, DEU = Germany, HKG = Hong Kong, IO = innovational outlier, JPN = Japan, m = month, USA = United States.
Notes: The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The figures in parentheses are t-statistics. The break points indicate the estimated year and month when the structural breaks are identified. Bold letters indicate significantly negative coefficients in 2020, while grey indicates significantly positive coefficients.
Source: UN, UN Comtrade Database, https://comtradeplus.un.org/ (accessed 12/30/2022).

Table 11: Break Points of the Number of Machinery Export Destination Countries – ASEAN Member States

AO model					
	IDN	MMR	MYS	SGP	VNM
Break point 1	2018m4	2017m2	**2020m2**	2017m12	2016m10
	0.035***	0.406***	**-0.083*****	0.029***	0.013***
	(4.217)	(6.238)	**(-5.653)**	(5.392)	(3.066)
Break point 2	**2020m3**	2019m10	2020m7	**2020m2**	2021m1
	-0.049***	-0.172***	0.078***	**-0.013****	0.009*
	(-5.091)	(-3.048)	(4.608)	**(-2.186)**	(1.693)
IO model					
	IDN	MMR	MYS	SGP	VNM
Break point 1	2018m2	2016m8	2019m12	2016m6	2016m11
	0.058***	0.225**	-0.099***	0.039***	0.015***
	(4.741)	(2.617)	(-5.434)	(3.630)	(2.916)
Break point 2	**2020m2**	**2020m12**	2020m6	2017m11	2021m2
	-0.078***	**-0.167***	0.092***	0.018***	0.014**
	(-5.701)	**(-1.963)**	(4.727)	(3.124)	(2.288)

AO = additive outlier, IDN = Indonesia, IO = innovational outlier, m = month, MMR = Myanmar, MYS = Malaysia, SGP = Singapore, VNM = Viet Nam.
Notes: The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The figures in parentheses are t-statistics. The break points indicate the estimated year and month when the structural breaks are identified. Bold letters indicate significantly negative coefficients in 2020, while grey indicates significantly positive coefficients.
Source: UN, UN Comtrade Database, https://comtradeplus.un.org/ (accessed 12/30/2022).

As discussed earlier, PageRank centrality – Equation (3) – increases when (i) the number of country i's partners increases, (ii) country i's trade increases, and 3) PageRank for country i's partner increases. Table 2 indicates that the negative shock of the pandemic on the machinery exports of Japan was temporal. Table 10 presents no significant negative effects of the pandemic on the number of machinery export destination countries in 2020. These results together suggest that the decline in Japan's centrality was not caused by the decline in export values nor the number of its destination countries. Rather, it is attributable to the decline in the centrality of Japan's export destination countries such as AMS. Indeed, Table 11 confirms the decline in the PageRank of AMS in 2020. Noting that Japan has a relatively strong trade relationship with AMS, these results together suggest that the negative shock of the pandemic spread throughout the supply chain, which led to the decline in the relative importance of some countries – such as Japan – in the world machinery trade network.

5. Concluding Remarks

In light of the importance of machinery trade in global trade, this study examined whether the patterns of machinery trade changed significantly after the COVID-19 pandemic outbreak. To do so, the framework of the network analysis was applied to identify the relative importance of each country in global machinery trade, and the framework of structural break was applied to statistically detect structural change in the machinery trade as well as the centrality.

The main findings are threefold. First, a positive structural change in exports in the major machinery-exporting countries was found. Second, negative structural changes in the centrality of Japan and some AMS were found, which imply the decline in the relative importance of these countries in the world machinery export network. Third, the decline in Japan's centrality was not caused by a decline in export values or number of destination countries. Rather, it is attributable to the decline in the centrality of Japan's export destination countries such as AMS. Noting that Japan has a relatively strong trade relationship with AMS, these results together suggest that the negative shock of the pandemic spread throughout the supply chain, which led to the decline in the relative importance of some countries – such as Japan – in the world machinery trade network.

In sum, the global machinery trade network was basically resilient against the pandemic. However, this is not applicable to all countries. Some were negatively affected by the pandemic, and their relative importance in the world machinery trade network declined. While only indicative, these results suggest the transmission of negative shocks throughout the supply chain during the pandemic. This finding is important because when overall trade is the focus, Kiyota (2022) did not find negative structural change in 2020. This study's results thus suggest the importance of detailed disaggregated-level analysis. In this context, the difference between the exports of intermediate goods and those of consumption goods should also be studied.

References

Acemoglu, D., V.M. Carvalho, A. Ozdaglar, and A. Tahbaz-Salehi (2012), 'The Network Origins of Aggregate Fluctuations', *Econometrica*, 80(5), pp.1977–2016.

Ando, M., F. Kimura, and A. Obashi (2021), 'International Production Networks Are Overcoming COVID-19 Shocks: Evidence from Japan's Machinery Trade', *Asian Economic Papers*, 20(3), pp.40–72.

Ando, M., F. Kimura, and K. Yamanouchi (2022), 'East Asian Production Networks Go beyond the Gravity Prediction,' *Asian Economic Papers*, 21(2), pp.78–101.

Ando, M. and K. Hayakawa (2022), 'Impact of COVID-19 on Trade in Services', *Japan and the World Economy*, 62, pp.101131.

Antonietti, R. et al. (2022), 'The World Trade Network: Country Centrality and the COVID-19 Pandemic,' *Applied Network Science*, 7(1), p.18.

Arriola, C., P. Kowalski, and F. van Tongeren (2021), 'The Impact of COVID-19 on Directions and Structure of International Trade', *Organisation for Economic Co-operation and Development (OECD) Trade Policy Papers,* No. 252, Paris: OECD.

Banerjee, A., R.L. Lumsdaine, and J.H. Stock (1992), 'Recursive and Sequential Tests of the Unit-Root and Trend-Break Hypotheses: Theory and International Evidence,' *Journal of Business and Economic Statistics*, 10(3), pp.271–87.

Carvalho, V.M. (2014), 'From Micro to Macro via Production Networks', *Journal of Economic Perspectives*, 28(4), pp.23–48.

Clemente, J., A. Montañés, and M. Reyes (1998), 'Testing for a Unit Root in Variables with a Double Change in the Mean', *Economics Letters*, 59(2), pp.175–82.

Freeman, R. and R. Baldwin (2022), 'Global Supply Chain Risk and Resilience', VoxEU Centre for Economic Policy Research, 6 April.

Hayakawa, K. and H. Mukunoki (2021), 'Impact of COVID-19 on Global Value Chains', *Developing Economies*, 59(2), pp.154–77.

International Monetary Fund (IMF) (2022), *World Economic Outlook Update: Rising Caseloads, Disrupted Recovery, and Higher Inflation*, Washington, DC.

Kiyota, K. (2022), 'The COVID-19 Pandemic and the World Trade Network', *Journal of Asian Economics*, 78, p.101419.

——— (2023), 'The Anatomy of a Global Network of Multinationals: The Case of Japan', unpublished.

Lumsdaine, RL. and D.H. Papell (1997), 'Multiple Trend Breaks and the Unit-Root Hypothesis,' *Review of Economics and Statistics*, 79(2), pp.212–18.

Page, L., S. Brin, R. Motwani, and T. Winograd (1999), 'The PageRank Citation Ranking: Bringing Order to the Web', *Stanford InfoLab Technical Reports,* No. 1999-66, Stanford: Stanford University.

Perron, P. and T.J. Vogelsang (1992), 'Nonstationarity and Level Shifts with an Application to Purchasing Power Parity', *Journal of Business and Economic Statistics*, 10(3), pp.301–20.

United Nations (UN), UN Comtrade Database, https://comtradeplus.un.org/ (accessed 12/30/2022).

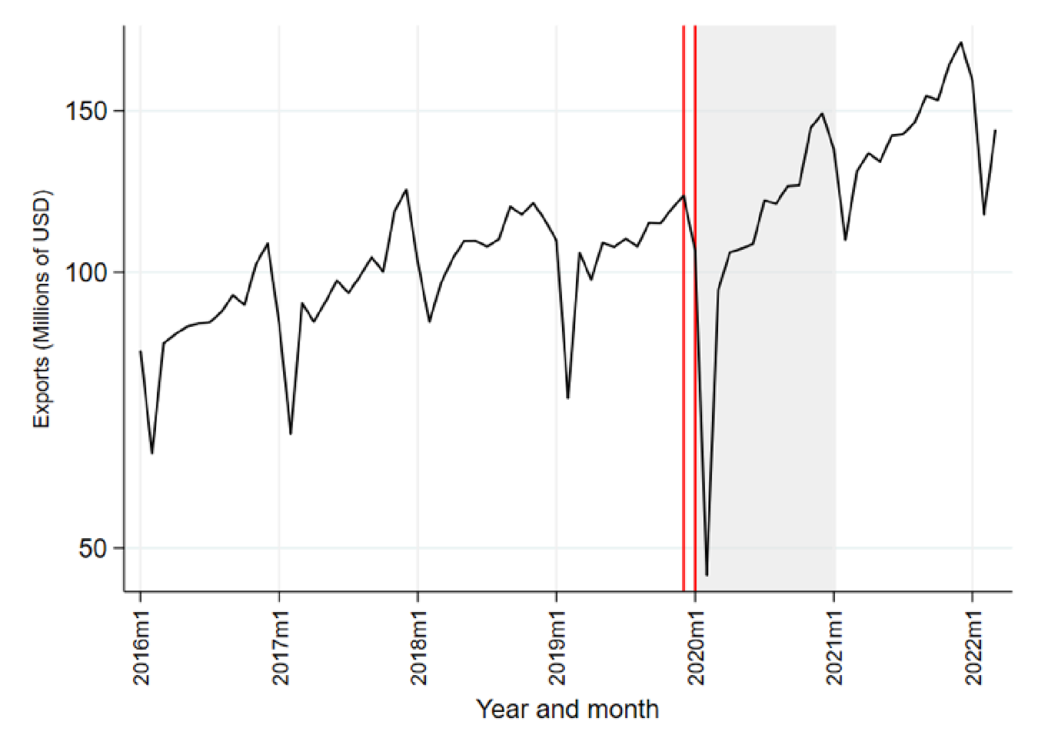
Vidya, C.T. and K.P. Prabheesh (2020), 'Implications of COVID-19 Pandemic on the Global Trade Networks,' *Emerging Markets Finance and Trade*, 56(special issue), pp.2408–21.

White House (2022) *Economic Report of the President*, April, Washington, DC.

Zivot, E. and D.W.K. Andrews (1992), 'Further Evidence on Great Crash, the Oil-Price Shock, and the Unit-Root Hypothesis,' *Journal of Business and Economic Statistics*, 10(3), pp.251–70.

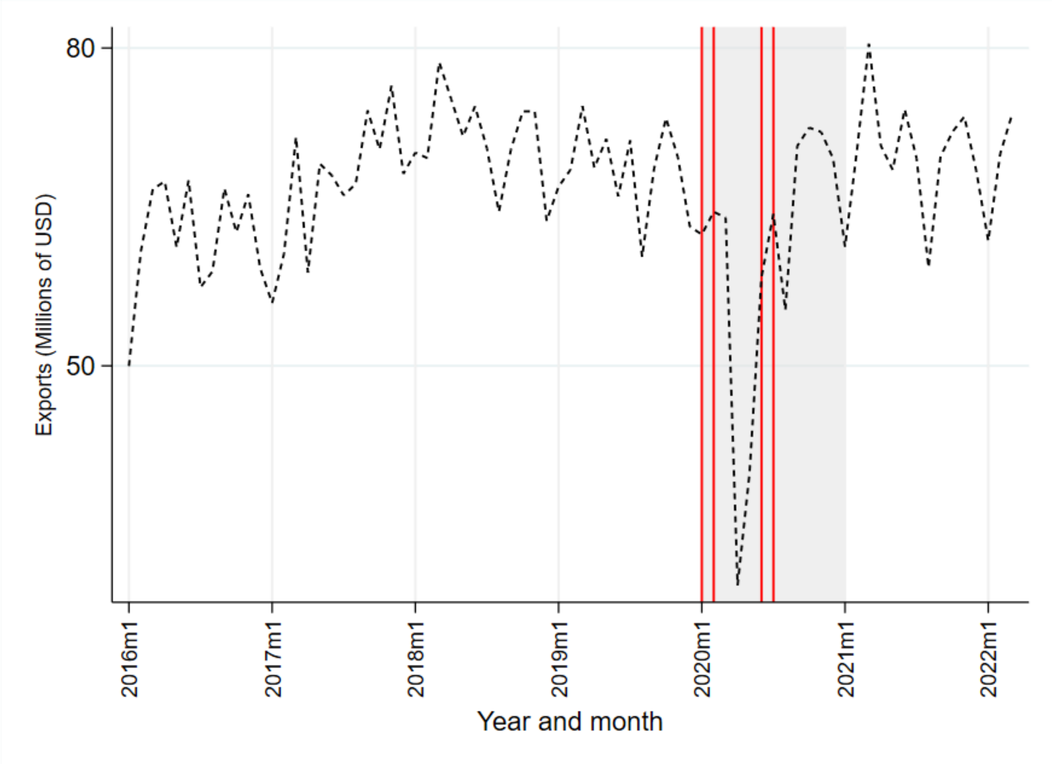
Appendix 1: Individual Country Machinery Exports, Break Points, and PageRank Centrality

Figure A1.1: Machinery Exports and Estimated Break Points, China
($ million)



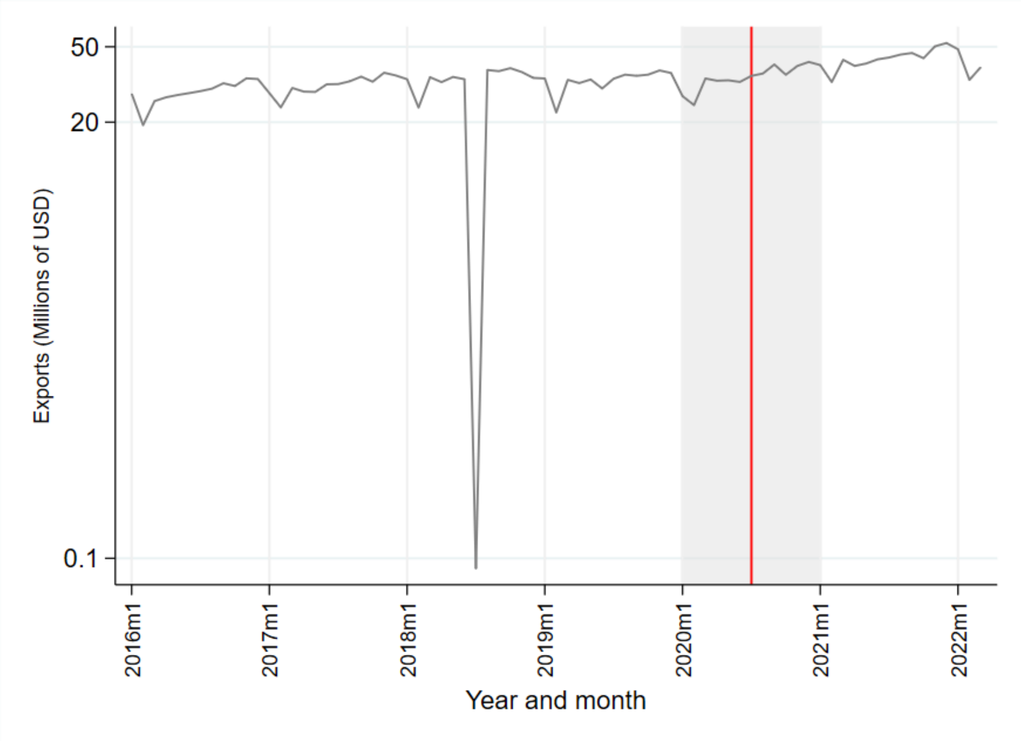
AO = additive outlier, IO = innovational outlier, M = month.
Note: Chinese export data are not available from October 2012 to December 2015 in the UN Comtrade Database. The grey area indicates 2020. The red lines indicate the estimated breakpoints by the AO or IO model. They are not distinguished, because sometimes both the AO and IO models estimated the same break points.
Source: UN, UN Comtrade Database, https://comtradeplus.un.org/ (accessed 12/30/2022).

Figure A1.2: Machinery Exports and Estimated Break Points, Germany
($ million)



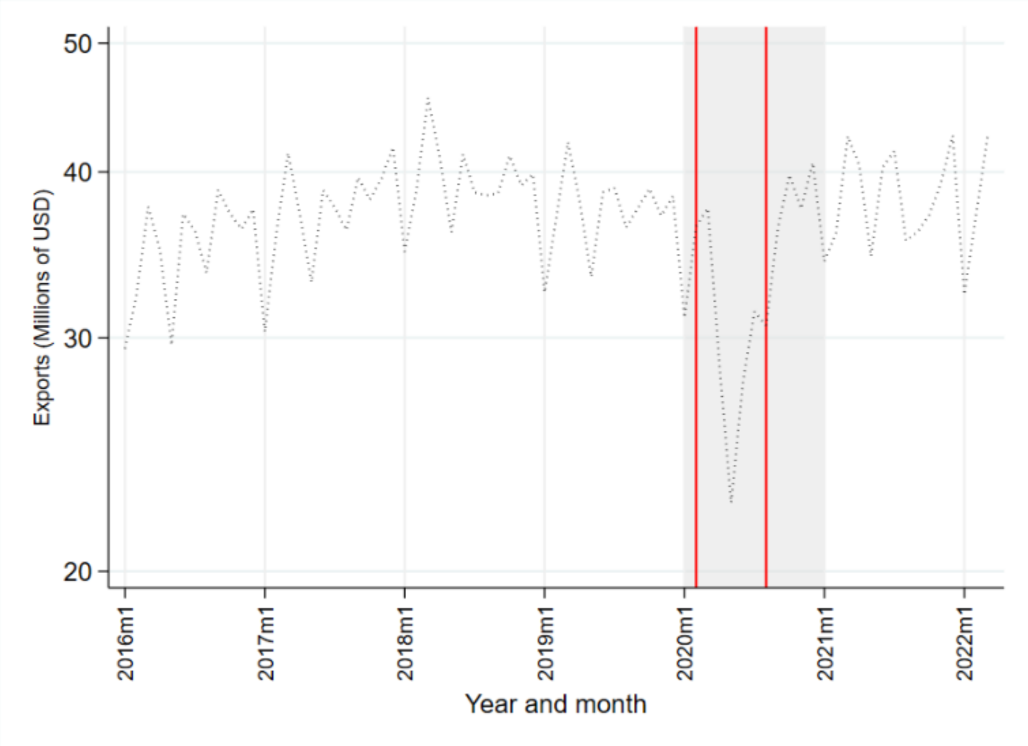
AO = additive outlier, IO = innovational outlier, M = month.
Note: The grey area indicates 2020. The red lines indicate the estimated breakpoints by the AO or IO model. They were not distinguished, because sometimes both the AO and IO models estimated the same break points.
Source: UN, UN Comtrade Database, https://comtradeplus.un.org/ (accessed 12/30/2022).

Figure A1.3: Machinery Exports and Estimated Break Points, Hong Kong
($ million)



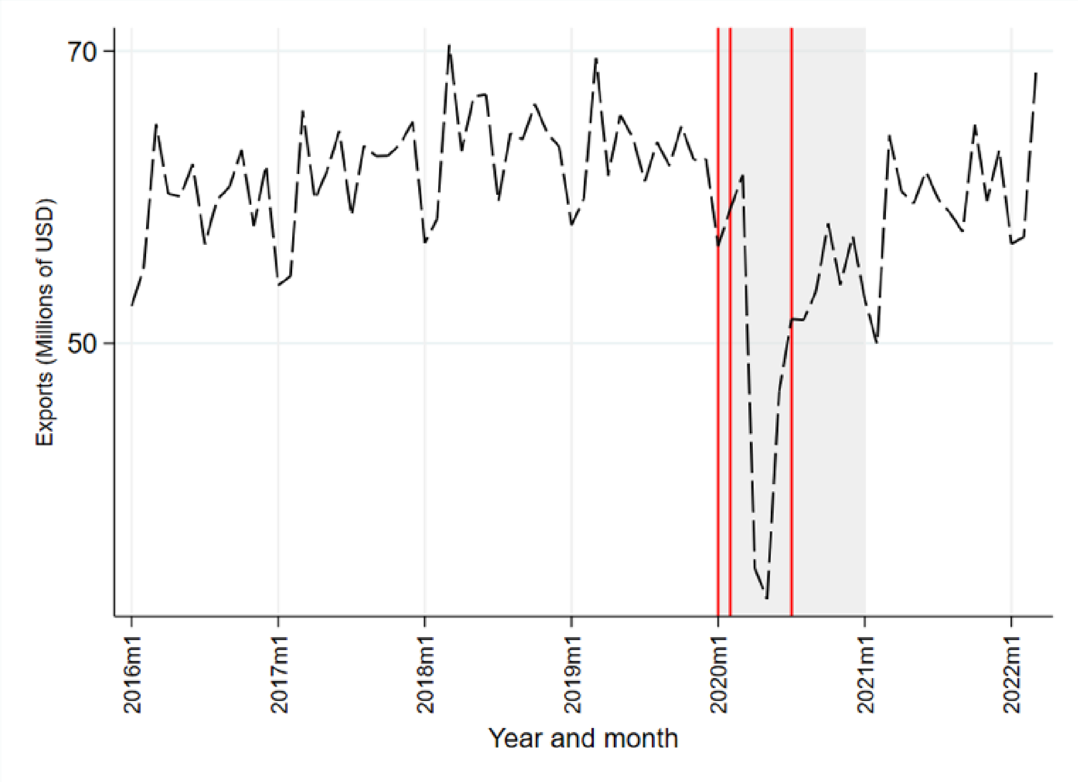
AO = additive outlier, IO = innovational outlier, M = month.
Note: The exports of many machinery products, including electrical machinery and transport equipment, are missing for Hong Kong in July 2018 in the UN Comtrade Database. The grey area indicates 2020. The red lines indicate the estimated breakpoints by the AO or IO model. They are not distinguished, because sometimes both the AO and IO models estimated the same break points.
Source: UN, UN Comtrade Database, https://comtradeplus.un.org/ (accessed 12/30/2022).

Figure A1.4: Machinery Exports and Estimated Break Points, Japan
($ million)



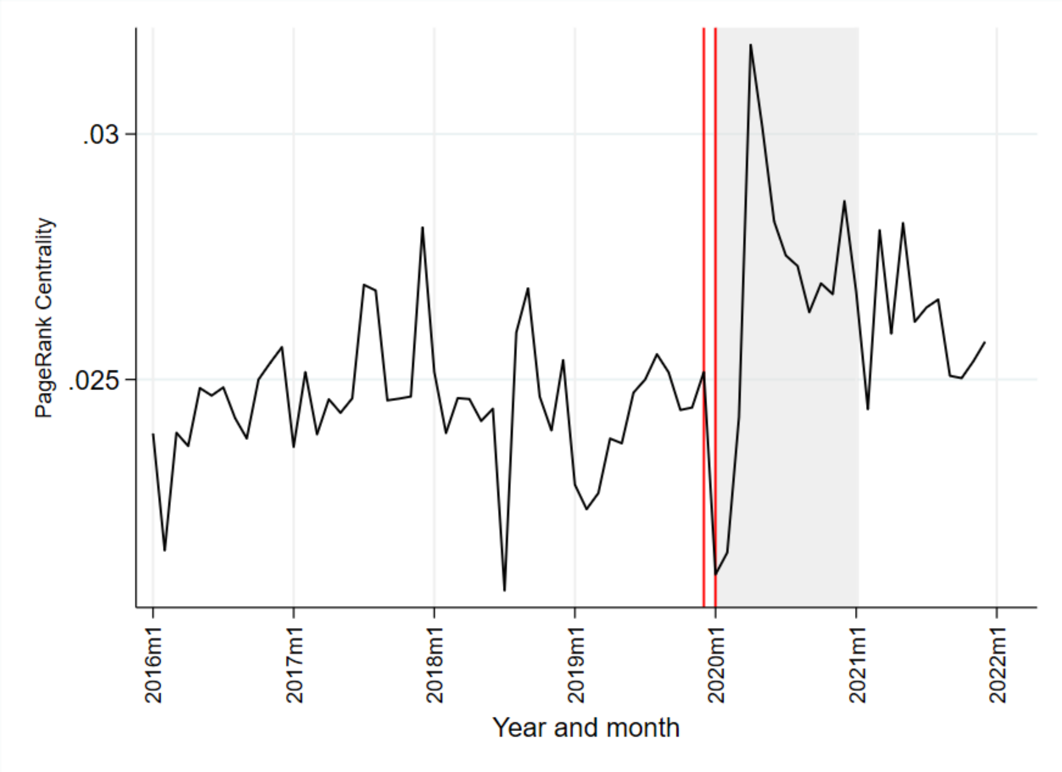
AO = additive outlier, IO = innovational outlier, M = month.
Notes: The grey area indicates 2020. The red lines indicate the estimated breakpoints by the AO or IO model. They are not distinguished, because sometimes both the AO and IO models estimated the same break points.
Source: UN, UN Comtrade Database, https://comtradeplus.un.org/ (accessed 12/30/2022).

Figure A1.5: Machinery Exports and Estimated Break Points, United States
($ million)



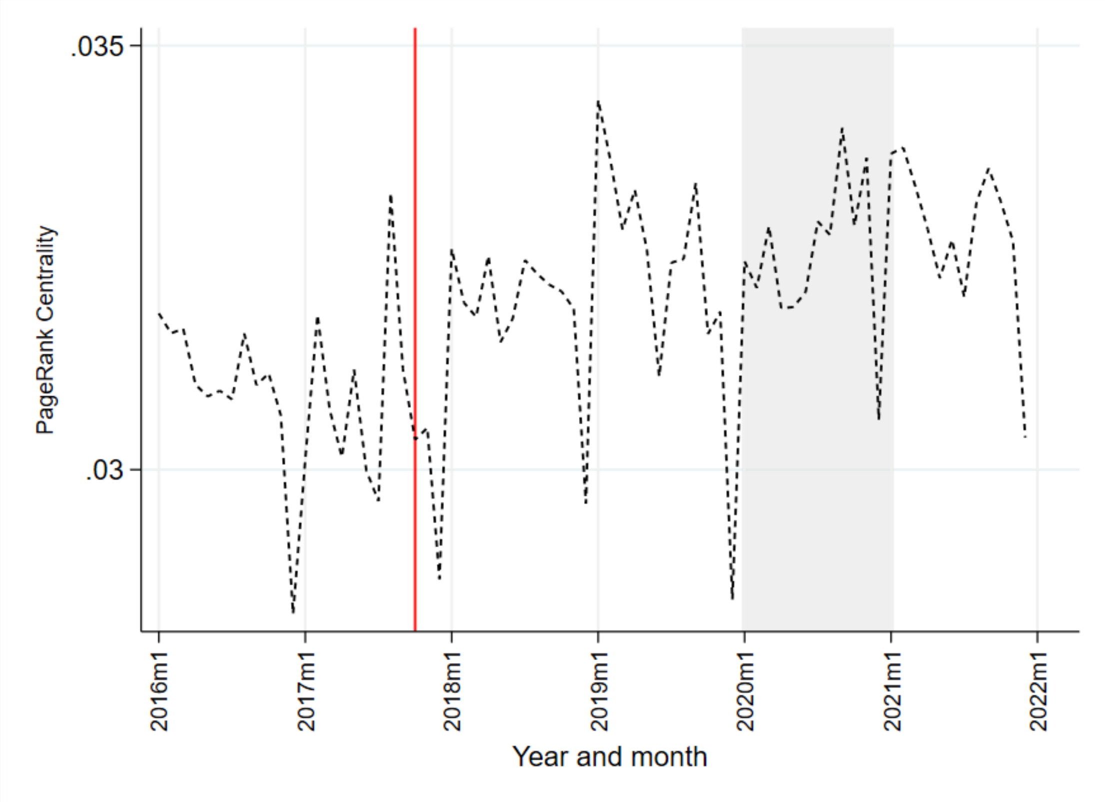
AO = additive outlier, IO = innovational outlier, M = month.
Notes: The grey area indicates 2020. The red lines indicate the estimated breakpoints by the AO or IO model. They are not distinguished, because sometimes both the AO and IO models estimated the same break points.
Source: UN, UN Comtrade Database, https://comtradeplus.un.org/ (accessed 12/30/2022).

Figure A1.6: PageRank Centrality and Estimated Break Points, China



AO = additive outlier, IO = innovational outlier, M = month.
Notes: The grey area indicates 2020. The red lines indicate the estimated breakpoints by AO or IO model. They are not distinguished, because sometimes both the AO and IO models estimated the same break points.
Source: UN, UN Comtrade Database, https://comtradeplus.un.org/ (accessed 12/30/2022).

Figure A1.7: PageRank Centrality and Estimated Break Points, Germany

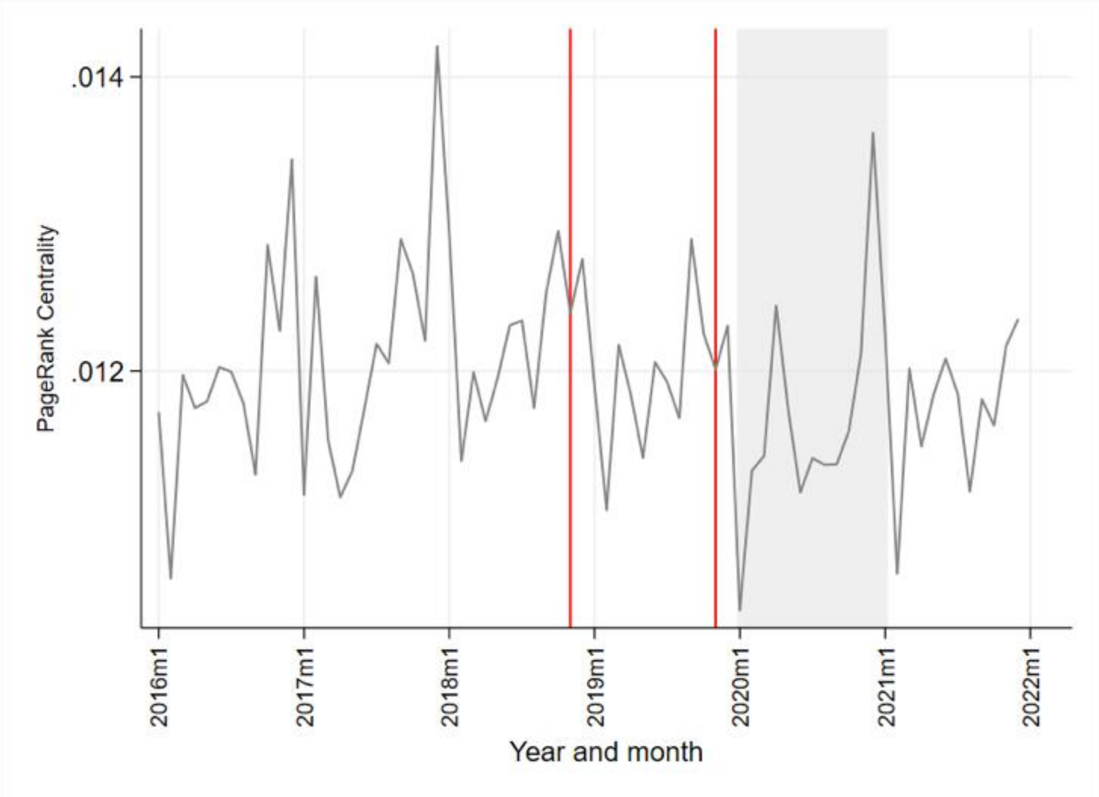


AO = additive outlier, IO = innovational outlier, M = month.

Notes: The grey area indicates 2020. The red lines indicate the estimated breakpoints by the AO or IO model. They are not distinguished, because sometimes both the AO and IO models estimated the same break points.

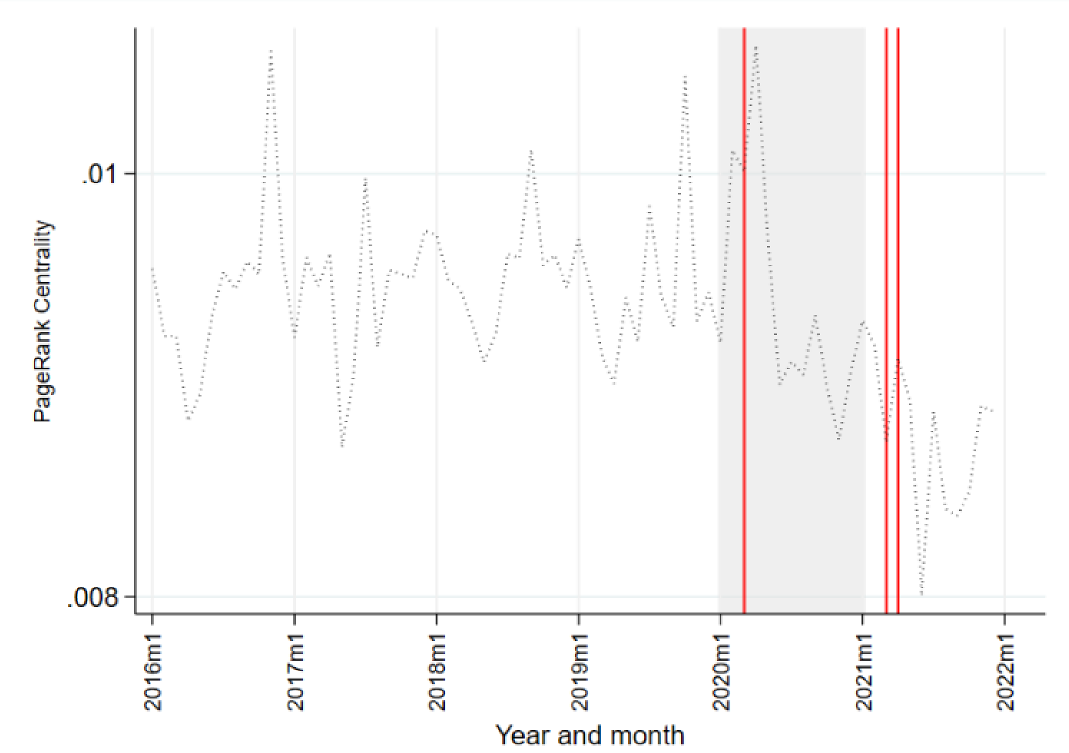
Source: UN, UN Comtrade Database, https://comtradeplus.un.org/ (accessed 12/30/2022).

Figure A1.8: PageRank Centrality and Estimated Break Points, Hong Kong



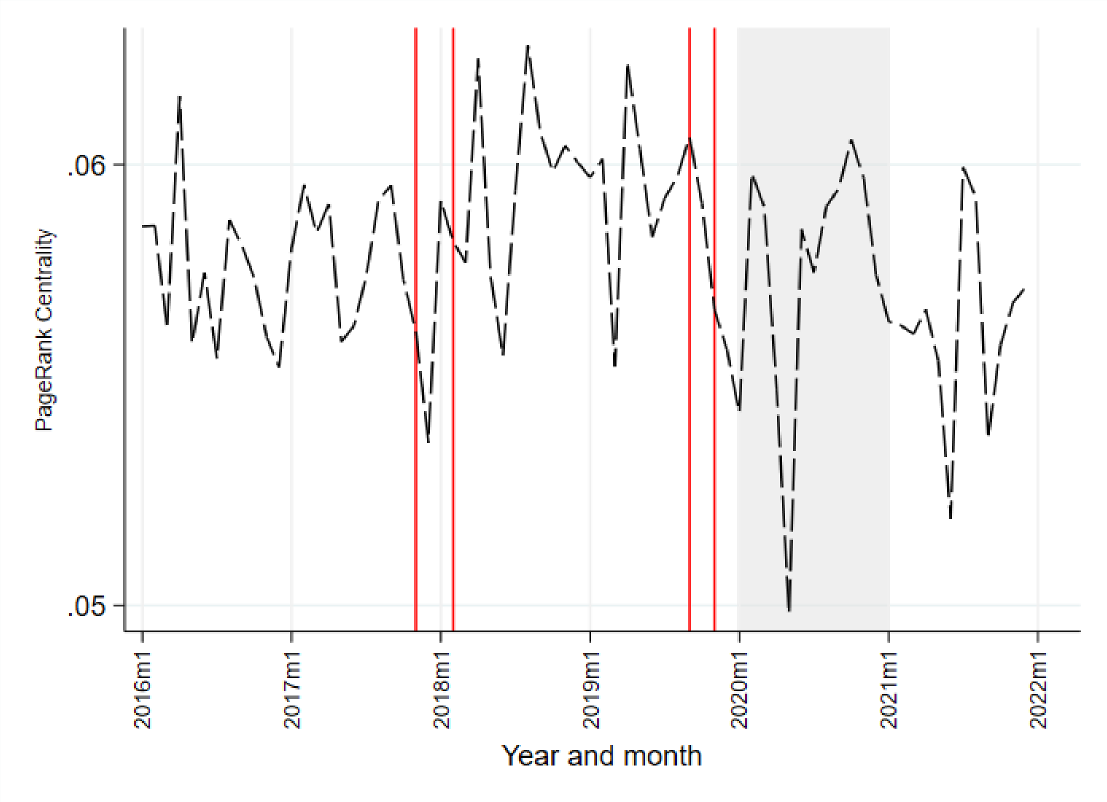
AO = additive outlier, IO = innovational outlier, M = month.
Notes: The grey area indicates 2020. The red lines indicate the estimated breakpoints by the AO or IO model. They are not distinguished, because sometimes both the AO and IO models estimated the same break points.
Source: UN, UN Comtrade Database, https://comtradeplus.un.org/ (accessed 12/30/2022).

Figure A1.9: PageRank Centrality and Estimated Break Points, Japan



AO = additive outlier, IO = innovational outlier, M = month.
Notes: The grey area indicates 2020. The red lines indicate the estimated breakpoints by the AO or IO model. They are not distinguished, because sometimes both the AO and IO models estimated the same break points.
Source: UN, UN Comtrade Database, https://comtradeplus.un.org/ (accessed 12/30/2022).

Figure A1.10: PageRank Centrality and Estimated Break Points, United States



AO = additive outlier, IO = innovational outlier, M = month.
Notes: The grey area indicates 2020. The red lines indicate the estimated breakpoints by the AO or IO model. They are not distinguished, because sometimes both the AO and IO models estimated the same break points.
Source: UN, UN Comtrade Database, https://comtradeplus.un.org/ (accessed 12/30/2022).

Appendix 2: Break Points Concerning Imports

Table A2.1: Break Points of Machinery Imports – Major Machinery-Exporting Countries

AO model	CHN	DEU	HKG	JPN	USA
Break point 1	2018m12	**2020m1**	2020m8	2019m11	**2020m1**
	-0.014	**-0.077*****	0.065***	-0.039***	**-0.085*****
	(-0.860)	**(-4.882)**	(3.209)	(-3.082)	**(-5.462)**
Break point 2	2020m8	2020m7	2021m4	2020m9	2020m7
	0.104***	0.113***	0.050**	0.070***	0.122***
	(6.163)	(6.766)	(2.031)	(5.005)	(7.427)
IO model	**CHN**	**DEU**	**HKG**	**JPN**	**USA**
Break point 1	2019m1	2020m2	2020m7	2019m12	2019m12
	-0.054***	-0.157***	0.084***	-0.074***	-0.065***
	(-3.010)	(-6.938)	(3.456)	(-4.982)	(-4.212)
Break point 2	2020m7	2020m7	2021m4	2020m8	2020m4
	0.117***	0.199***	0.073	0.103***	0.085***
	(4.730)	(7.417)	(1.416)	(5.919)	(5.235)

AO = additive outlier, CHN = China, DEU = Germany, HKG = Hong Kong, IO = innovational outlier, JPN = Japan, m = month, USA = United States.

Notes: The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The figures in parentheses are t-statistics. The break points indicate the estimated year and month when the structural breaks are identified. Bold letters indicate significantly negative coefficients in 2020, while grey indicates significantly positive coefficients.

Source: UN, UN Comtrade Database, https://comtradeplus.un.org/ (accessed 12/30/2022).

Table A2.2: Break Points of the Centrality of Machinery Imports – Major Machinery-Exporting Countries

AO model					
	CHN	DEU	HKG	JPN	USA
Break point 1	2019m12	2019m7	2018m3	2019m2	**2020m2**
	0.084***	-0.051***	0.098***	-0.049***	**-0.107*** **
	(4.900)	(-6.368)	(3.826)	(-3.389)	**(-9.364)**
Break point 2	2021m8	2021m8	2018m11	2020m2	2021m10
	0.077***	-0.060***	0.004	-0.017	-0.051**
	(2.863)	(-4.768)	(0.197)	(-1.175)	(-2.468)

IO model					
	CHN	DEU	HKG	JPN	USA
Break point 1	2020m1	2019m4	2018m2	2018m7	**2020m3**
	0.080***	-0.041***	0.110**	-0.044***	**-0.094*** **
	(4.830)	(-4.239)	(2.660)	(-2.915)	**(-5.968)**
Break point 2	2021m5	2021m6	2018m12	**2020m3**	2021m7
	0.072***	-0.053***	-0.005	**-0.050*** **	-0.026*
	(3.222)	(-3.951)	(-0.148)	**(-3.327)**	(-1.762)

AO = additive outlier, CHN = China, DEU = Germany, HKG = Hong Kong, IO = innovational outlier, JPN = Japan, USA = United States.
Notes: The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The figures in parentheses are t-statistics. The break points indicate the estimated year and month when the structural breaks are identified. Bold letters indicate significantly negative coefficients in 2020, while grey indicates significantly positive coefficients.
Source: UN, UN Comtrade Database, https://comtradeplus.un.org/ (accessed 12/30/2022).

ERIA Discussion Paper Series

No.	Author(s)	Title	Year
2023-09 (No. 481)	Yoko KONISHI and Takashi SAITO	What Japanese Tourism Amenities Are Influenced in Terms of Affecting Inbound Tourist Demand?	August 2023
2023-08 (No. 480)	Shandre Mugan THANGAVELU, Leng SOKLONG, Vutha HING, and Ratha KONG	Investment Facilitation and Promotion in Cambodia: Impact of Provincial-level Characteristics on Multinational Activities	August 2023
2023-07 (No. 479)	Diep PHAN and Ian COXHEAD	Capital Cost, Technology Choice, and Demand for Skills in Industries in Viet Nam	July 2023
2023-06 (No. 478)	Shandre Mugan THANGAVELU	Structural Changes and the Impact of FDI on Singapore's Manufacturing Activites	June 2023
2023-05 (No. 477)	Yanfei LI, Jia ZHAO, and Jianjun YAN	Technological Innovation and the Development of the Fuel Cell Electric Vehicle Industry Based on Patent Value Analysis	June 2023
2023-04 (No. 476)	Etsuyo MICHIDA	Effectiveness of Self-Regulating Sustainability Standards for the Palm Oil Industry	June 2023
2023-03 (No. 475)	Ian COXHEAD and Nguyen Dinh Tuan VUONG	Does the Skill Premium Influence Educational Decisions? Evidence from Viet Nam	May 2023
2023-02 (No. 474)	Ha Thi Thanh DOAN, Kunhyui KIM and Mahdi GHODSHI	Divergence in Non-Tariff Measures and the Quality of Traded Products	May 2023
2023-01 (No. 473)	Dionisius A. NARJOKO	Foreign Direct Investment, Agglomeration, and Production Networks in Indonesian Manufacturing	May 2023
2022-43 (No. 472)	Peter WARR and Huy Quynh NGUYEN	Productivity Effects of Viet Nam's Rice Land Restrictions	March 2023
2022-42 (No. 471)	Yuki HIGUCHI, Vu Hoang NAM, and Tetsushi SONOBE	Do Management Interventions Last? Evidence from Vietnamese SMEs	March 2023
2022-41 (No. 470)	Huong-Giang PHAM, Tuong-Anh T. NGUYEN, and Hoang-Nam VU	Adoption of Sustainable Practices for Improving Agricultural Productivity in Viet Nam	March 2023
2022-40 (No. 469)	Quang Hoan TRUONG and Van Chung DONG	Impacts of FDI Presence and Product Sophistication on the Demand for Skilled and Unskilled Labour: Evidence from SMEs in Viet Nam	March 2023
2022-39 (No. 468)	Araba SEY	Availability of Gender-Disaggregated Data on the ASEAN Digital Economy	January 2023
2022-38 (No. 467)	Yose R. DAMURI and Deni FRIAWAN	RCEP and Indonesia: Economic Reform and Prospects for Implementation	January 2023

ERIA discussion papers from previous years can be found at:
http://www.eria.org/publications/category/discussion-papers